Diffusion of a gear-based conservation innovation: adoption patterns and social - ecological outcomes

Thesis submitted by

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This thesis is dedicated to my late father, Harold Prestone Mbaru. Your love, affection, dedication, our memories will remain forever in our hearts.

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Executive summary

Conservation interventions are only effective if people use them. Thus, identifying motivations and barriers to the uptake of conservation interventions is critical. Yet, analysis of factors that hinder or promote conservation diffusion (spread of conservation interventions) processes has received little attention by conservation practitioners and policy makers. Consequently, many efforts to achieve sustainability fail to reach full potential.

Nearly all conservation interventions are characterized by the introduction of new ideas and practices. In line with this recognition, implementation of conservation can therefore benefit from a large body of social science research that explains how new ideas, practises, and technologies, i.e., innovations[1] spread. Central to understanding how innovations spread among social systems, is the diffusion of innovations theory[2] pioneered by Rogers. This thesis uses the diffusion of innovation lens to investigate the introduction of a conservation intervention in coastal Kenya.

Diffusion research show that peoples' adoption behaviour is typically influenced by social differentiations in terms of personal attributes, socioeconomic status, and communication behaviour (Rogers 2010). Though personal attributes and socioeconomic status are widely used to analyse adoption processes (Horst et al 2007, Knowler & Bradshaw 2007), there remains very limited empirical work emphasizing the effect of communication behaviour in conservation diffusion literature. In addition, there is a long-standing recognition that proper communication channels[3] are critical in facilitating innovation transfer (Gladwell 2006, Nilakanta & Scamell 1990, Rogers 1995). Yet, no criteria currently exist in the conservation

[1] An idea, practice or object that is perceived as new by individuals, groups, or other units of adopters (e.g., organizations) (Rogers 1995).

[2] Diffusion of innovations is defined as the process by which a novel idea, technology, or practice is communicated through certain channels over time among members of a social system (Rogers 1995).

[3] Means by which innovations move from individual to individual, group to group, or organizations to organizations (Rogers 1995).

literature to identify characteristics and functions of key intermediaries needed to facilitate conservation transfer. Thirdly, after initial adoption, whether people maintain an innovation is largely determined by the impact it has on their lives. However, conservation diffusion studies rarely examine the impacts of conservation innovations on either people or ecosystems (Weeks et al 2010, Woodhouse & Emiel de Lange 2016). These critical knowledge gaps lend themselves for empirical investigation.

This thesis therefore aims to examine how people adopt conservation interventions and determine key social and environmental impacts of doing so. To address these aims, I ask two fundamental research questions: *(i) "how does conservation interventions spread through societies?" (ii) "what are the consequences of conservation diffusion on people and environment?"*

I provide answers to these questions by addressing the following interrelated specific objectives:

1. determine the factors that influence uptake (adoption) and spread (diffusion) of a conservation intervention over time (Chapter 3)
2. identify key stakeholders to facilitate conservation transfer (Chapter 4)
3. investigate impacts of conservation diffusion on people‘s wellbeing (Chapter 5)
4. examine impacts of conservation diffusion on the ecosystem (Chapter 6)

I explore these issues through a case study of a fisheries bycatch (incidental take) reduction initiative introduced in coastal Kenya (see details in chapter 2). Specifically, I study a modified basket trap retrofitted with escape gaps that allows juveniles and narrow-bodied, low value fish species (i.e. bycatch) to exit, while larger, wider-bodied target species are retained (Mbaru & McClanahan 2013). This intervention was introduced with the explicit aim to protect biodiversity by harvesting fish species at sizes that ensure sustainability of the local fishery (McClanahan & Mangi 2004). However, it was expected that improved catches over time will translate to positive sustainability outcomes, e.g., improved income and livelihoods that will continue to accrue over the long term.

Aside from the diffusion of innovations theory, this research further draws from a number of social science theories and emerging breakthroughs in functional ecology to provide a rigorous and deeper examination of the study aims highlighted above. Chapter 1 provides a general introduction about the different theoretical foundations and approaches that can be used to analyse conservation diffusion processes in light of the diffusion of innovations theory. Chapter 2 provides an overview of study sites and describes the methods used throughout the thesis, though each chapter will also have additional methods.

In chapter 3, I integrate theoretical foundations of the diffusion of innovations theory with novel breakthroughs in network science to offer a clearer understanding of the factors that shape conservation diffusion patterns over time. Unlike the majority of conservation diffusion studies, I explicitly measure communication behaviour via social networks[4] and leverage recent advances in network modelling to simultaneously test the effect of social network structures and social influence on conservation diffusion while accounting for personal attributes and socioeconomic characteristics. I show that network processes contribute considerably to conservation diffusion – particularly in the early adoption stage – even when key socioeconomic factors are accounted for. By showing that communication behaviour is crucial during the early stages of the diffusion process, my results challenge decades of diffusion research suggesting commination behaviour is more important for late adoption. Overall, I demonstrate that harnessing the power and characteristics of social networks can help diffuse conservation interventions through target populations.

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[4] The notion that individuals are embedded within a larger context of relational ties (Borgatti et al 2009).

In chapter 4, I draw on social network theory and methods to develop specific criteria for selecting stakeholders who are best placed in social networks (i.e., key players) to facilitate four key conservation objectives: (1) rapid diffusion of conservation information, (2) diffusion between disconnected groups, (3) rapid diffusion of complex knowledge or initiatives, or (4) widespread diffusion of conservation information or initiatives over a longer time period. After identifying the key players for the four distinct diffusion related conservation objectives, I then test whether the socioeconomic attributes of the key players I identified match the ones typically selected by conservation NGOs and other resource management agencies to facilitate conservation diffusion (i.e., current players). Results show clear discrepancies between current players and key players, highlighting missed opportunities for progressing more effective conservation diffusion. The chapter concludes with a novel, practical, and nuance approach to identify a set of ‗key players' better positioned to facilitate diffusion related conservation objectives, thereby helping to mitigate the problem of stakeholder identification in conservation diffusion processes.

The focus of chapter 5 is to investigate the effects of adoption or non-adoption of the conservation intervention on people's wellbeing, i.e., an umbrella term that encompasses good social relations, freedom of choice, and basic materials for a good life (MEA 2005). Here, I use the wellbeing framework (Gough & McGregor 2007) to capture how the conservation innovation may impact multiple dimensions (material, relational, subjective) of people's wellbeing. I use panel data (i.e., follow the same individuals over time) to study these three dimensions of wellbeing before the intervention, during the short term (i.e., one year after the introduction), and in the medium term (i.e., about two years after the introduction) for those that adopt the innovation (adopters), those that don't adopt (non-adopters), and in control villages, where the intervention was not introduced. Overall, my findings indicate that adoption of the conservation intervention did no harm to the associated human communities. Indeed, I show modest improvements in material and subjective livelihood wellbeing for adopters relative to controls over time. However, the variations I find in wellbeing experiences (in terms of magnitude of change) among adopters, non-adopters, and controls across the different domains over time affirm the dynamic and social nature of wellbeing. Findings emphasize the need for environmental policy to use multiple indicators of wellbeing in addition to baselines in future evaluation research.

The focus of chapter 6 is to assess the impact of the conservation intervention on environment. Previous attempts have been made to understand the effects of escape slot trap fishing on the marine environment (Condy et al 2015). However, most of this work tends to focus on species abundances and catch composition (Gomes et al 2014). Yet, the growing interest in an ecosystem-based approach has stressed maintaining and sustaining ecological functions (Henriques et al 2014). Moreover, in multi-species coral reef fisheries fishing gears are known to exhibit some degree of overlap in the species they capture (McClanahan & Mangi 2001). Depending on the level and type of overlap, these interactions can potentially retard critical pathways associated with gear-based conservation interventions (McClanahan & Kosgei 2018). Against this background, I employ a trait-based approach to assess functional selectivity of the escape slot trap. In addition, I quantify overlaps in catch composition between escape slot traps and other gear types that operate concurrently in the same reefs. These are hook and line, speargun, gillnet, beach seine, basket trap, and a combination of other nets. Overall, I show that using escape slot traps has the potential to lead to environmental improvements. Fish assemblages in escape slot traps are more functionally redundant (tendency of species to perform similar functions) and a vast majority constitute the least breadth of functional diversity. However, I find that two-thirds of the catch released by escape slot traps is targeted by other gear types. Thus, given the extent of overlaps in species selectivity between gears, switching to escape slot traps may not achieve conservation targets in the Kenyan multi-species coral reef fishery unless other gear types are also simultaneously excluded. These results call for caution when assessing ecological implications of gear-based conservation innovations particularly in gear-diverse coral reef fisheries where competitive interactions between gears are eminent.

Together, this body of work advances the current state of knowledge about analysing patterns and outcomes of conservation diffusion over time. The stakeholder selection criteria developed in chapter 4 can be applied to facilitate widespread adoption and diffusion of simple initiatives such as rapid environmental awareness campaigns as well as more complex initiatives that seek to implement behaviour change to improve conservation outcomes. This work further provides a more comprehensive way to look at conservation outcomes and can help draw policy attention to the nonmaterial impacts of conservation. Trait-based approaches can provide a concrete platform for ecosystem-based management approaches in tropical multi-species fisheries.

Publications associated with this thesis

Chapter 4: **E. Mbaru** & M. Barnes (2017). Key players in conservation diffusion: using social network analysis to identify critical injection points. *Biological Conservation* 210: 222–232.

Chapter 6: **E. Mbaru,** N. Graham, T. McClanahan, J. Cinner. Functional traits illuminate the selective impacts of different fishing gears on coral reefs. (in 2nd round of reviews) *Journal of Applied Ecology.*

Chapter 3: E. Mbaru, M. Barnes, J. Cinner. Understanding conservation diffusion: Empirical results from a fisheries bycatch management initiative. (in prep). Target journal: Nature sustainability.

Chapter 5: E. Mbaru, J. Cinner, C. Hicks, G. Gurney. Evaluating outcomes of conservation using multidimensional indicators of wellbeing. (in prep). Target journal, Conservation Letters.

Other publications during PhD

E. Mbaru, D. Sigana, R. Ruwa, E. Mueni, C. Ndoro, E. Kimani, B. Kaunda-Arara (2018). Experimental evaluation of influence of FADs on community structure and fisheries in coastal Kenya. *Aquatic Living Resources* 31: 6.

B. Kaunda-Arara, C. Munga, J. Manyala, B. Kuguru, M. Igulu, M. Chande, S. Kangwe, S. Mwakiti, P. Thoya, **E. Mbaru,** R. Ruwa (2016). Spatial variation in benthopelagic fish assemblage structure along coastal East Africa from recent bottom trawl surveys. *Regional Studies in Marine Science* 8: 201-209.

M. Barnes, E. Mbaru, N. Muthiga. Information access and knowledge exchange in co-managed coral reef fisheries. (in 2nd round of reviews) *Biological Conservation.*

Table of contents

List of tables

List of figures

Appendix

Tables

Figures

Chapter 1: General introduction

Conservation diffusion gap

Ecosystems support immense biodiversity and provide important services to millions of people (Hicks & Cinner 2014, Pitcher et al 2009). Yet these ecosystems and the services they support are degrading rapidly in response to numerous anthropogenic disturbances (Hughes et al 2017). To stem these losses, research programs, NGOs, development agencies, and funding bodies have invested heavily in conservation (Dudley & Stolton 2010, Paehlke 2005). Here, I define conservation as planned preservation, protection, and management of a natural resource to prevent overexploitation or destruction.

Conservation practitioners often hope that successful conservation strategies will become widely adopted. However, limited uptake and transitory use of conservation interventions is increasingly becoming a major concern for conservation practitioners around the globe (Knowler & Bradshaw 2007). Understanding factors that might promote or constrain conservation diffusion (spread of novel conservation interventions) is clearly essential for the success of current and future conservation programs. However, identifying key determinants of adoption and diffusion can be challenging because people respond differently to socioeconomic factors when they consider whether or not to take up novel conservation ideas and practises (Padgett 2011, Tiwari et al 2008).

Problem statement

Many conservation interventions suffer poor rates of adoption because there is little understanding of how conservation ideas and practices spread through societies.

Diffusion of innovations theory

Nearly all conservation interventions are characterized by the introduction of new ideas and practices. Yet the implementation of conservation often fails to consider lessons from the decades of social science research that has studied patterns of adoption and diffusion of new ideas and practises (i.e., innovations) (Rogers 2003, Valente 1996a). Central to understanding how new messages, ideas, practises, or technologies (innovations) spread among social systems, is the diffusion of innovations theory (Rogers 2010). Diffusion of innovations is defined as the process by which a novel idea, technology, or practice is adopted through certain channels over time among members of a social system (Rogers 2003). Diffusion of innovation theory has evolved from its roots in rural sociology, education, and anthropology (Allen 1982, Dosi 1991), and is now applied across disciplines to study how and why novel interventions spread, as well as predict rates of adoption and diffusion over time (Banerjee et al 2013, Fuglie & Kascak 2001, Stoneman & Diederen 1994, Wejnert 2002). Key to the theory is the presence of four elements of diffusion that are identifiable in every diffusion research study, i.e., innovation, communication channels, social systems, and time

Innovation: Diffusion literature defines innovation as an idea, practice or object that is perceived as new by individuals, group, or other units of adopters (e.g., organizations) (Rogers 1995). In the conservation context, innovations could include output controls in fisheries management, reserves, or changes to waste management practices (Islam & Tanaka 2004, McClanahan 2010). Conservation can also take the form of technologies, e.g., fisheries technology improvements that reduce bycatch (Brewer et al 1998). Sociologists in the past attempted to make a distinction between innovation and technology. In support of their argument, they define technology as a design for instrumental action (Tutore et al 2014), and an innovation as an idea or object perceived as new by an individual (Rogers 2003). Based on this distinction, technological diffusion was described as the process by which innovations (e.g., new products, new processes, and new management methods) spread within and across economies (Stoneman & Diederen 1994). However, more recent additions of Rogers' diffusion of innovations theory contend that innovation and technology can be treated as synonyms because a majority of new ideas and practises are technological innovations (Rogers 2003).

Communication channels: Diffusion literature captures communication channels as the means by which innovations move from individual to individual, group to group, or organizations to organizations (Rogers 1995). In natural resource management settings, intermediaries who serve varied functions between authorities, experts, and local resource users are key channels of communication that can facilitate transfer of novel information, knowledge, and innovations (Prell et al 2009, Reed et al 2009). Their functions often include facilitating the flow of innovations between users and developers by linking potential adopters with experts or translating technical material into a more user friendly format (Gladwell 2006).

Social systems: Diffusion research defines a social system as a set of interrelated units that are engaged in joint problem solving activities to accomplish a goal or goals (Rogers 1995). In social-ecological settings, a co-managed fishery typify a social system where several stakeholders come together to solve natural resource problems cooperatively, e.g., overfishing. Social systems are rarely homogenous. Even in small-scale societies, there can be remarkable heterogeneity in socioeconomic conditions between individuals, groups, or organisations (Jackson & Lopez-Pintado 2013). Differences in socioeconomic identities observed in social systems underpin the existence of different adopter categories and patterns of adoption over time (Rogers 2010).

Time: Time is the non-spatial interval through which the diffusion events occur (Rogers 1995). These events include the relative span of time for the individual or group to adopt the innovation, the innovation-decision process, and the innovations‘ rate of adoption in a system (Rogers 2010). Adoption-decision process captures the period between innovation awareness to final adoption. For a potential adopter, the innovation-decision process may lead to adoption or rejection of the innovation. When adoption occurs, the rate of adoption among potential adopters follows a cumulative S-curve when plotted over time (Ryan & Gross 1943).

Adopter categories

Based on the time of adoption, diffusion of innovations theory classifies the diffusion process as consisting of five adopter categories; innovators (first, 2.5%), early adopters (second, 13.5%), early majority (third, 34%), late majority (fourth, 34%), and laggards (last, 16%) (Rogers 1995) (Fig. 1). In describing the characteristics of these categories, diffusion literature contend that differences exist between adopters at different stages of the distribution curve (Rogers 2010, Ryan & Gross 1943). Recent studies have however shown that stronger differences between adopter groups emerge when some adopter categories are merged (Diederen et al 2003). As a result, very recent diffusion studies consider innovators, early adopters, and early majority, *„early adopters"* whereas late majority and laggards are collectively classified as *„late adopters"*(Flaten et al 2006, Läpple & Van Rensburg 2011).

In any diffusion process, there are cases where people don‘t adopt innovations even when all evidence may suggest that they should (Guerin & Guerin 1994). Similarly, discontinuation or ‗dis-adoption‘ of innovation use can occur (Dinar & Yaron 1992). Several reasons that make individuals reject or give up innovations such as cost of the innovation, lack of profitability, insufficient subsidy have been highlighted (Dinar & Yaron 1992, Dinar & Yaron 2002). Following these revelations, classical diffusion studies contend that, at a minimum, there should be four important categories of adoption behaviour: early adopters, late adopters, non-adopters, and one that is often overlooked dis-adopters (those that adopt but later quit) (Barham et al 2004, D'Souza & Mishra 2018).

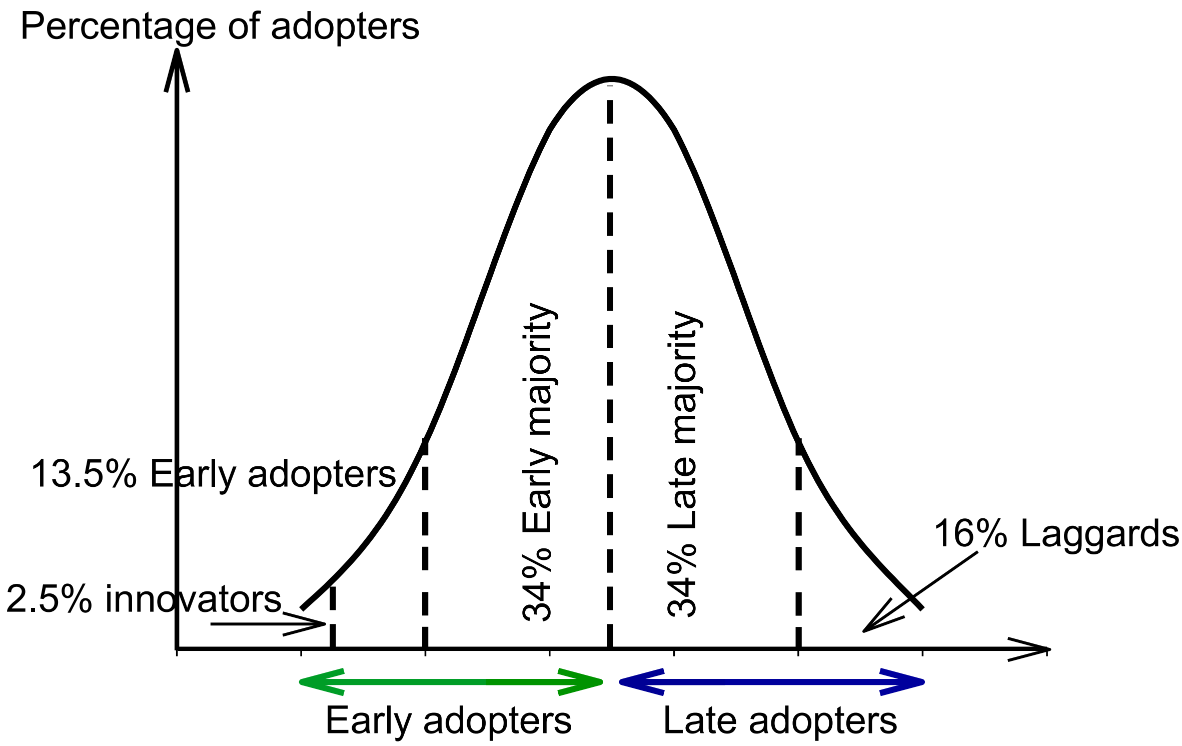

Figure 1. Innovation adopter categories of Rogers.

Characteristics of adopter categories

A critical focus of many diffusion studies is exploring why some people adopt and others do not. Studies that examine the influence of various determinants on adoption and diffusion processes have identified three key categories of adoptee traits that influence spread of innovations and speed of adoption: personality traits, socioeconomic status, and communication behaviour (Dearing & Cox 2018, Feder & Umali 1993, Gine & Klonner 2008, Tingley & Pascoe 2005). The next paragraphs below highlight the general overview of these attributes. A more detailed review of these attributes is provided in chapter 2.

Personality traits

Many adoption studies often correlate personality characteristics such as risk orientation, rationality or agency, psychological strength, self-confidence, and others with innovation adoption behaviour (Feder 1980, Goldsmith 1984, Shields & Rauniyar 1993, Torres-Irineo et al 2014, Vanclay & Lawrence 1994). The emphasis on personality traits is underpinned by the notion that innovations would spread more rapidly among members who perceive them to be advantageous regardless of whether or not those innovations have objective advantages (Rogers 2010).

Socioeconomic status

Taking a broad view on socioeconomic status, diffusion research demonstrate that differences in people‘s socioeconomic status account for more variance in likelihood of an individual's adoption behaviour than a vast majority of sociodemographic variables such as age, race, ethnicity, marital status, and gender (Halim 2002, Morris & Venkatesh 2000, Muldoon 2009). Attributes of socioeconomic status such as wealth, education, occupational diversity/multiplicity, size of firm, and ownership of key productive assets have often been used to classify adopter categories (Feder & Umali 1993, Guerin & Guerin 1994, Knowler & Bradshaw 2007, Mercer 2004). However, like personality traits, socioeconomic status can have both positive and/or negative effects on adoption and diffusion of innovations across societies, showing either positive or negative relationships depending on the complexity of the innovation and the social identity[5] and experiences of the potential adopter (Ervin & Ervin 1982, Guerin & Guerin 1994, Knowler & Bradshaw 2007, Muldoon 2009, Prokopy et

[5] The social identity approach describes and explains the way groups of people interact with each other, and how an individual may adopt behavioural tendencies associated with other members of a group or become member of a group (Covin et al 2015, Lute & Gore 2014). Thus an individual‘s social identity is not simply a statement of who they are, but also describes how they perceive their place in social groups, and indicates the social norms to which they are likely to adhere (Haslam 2000, Unsworth & Fielding 2014). By offering implications for deliberations and decision-making, the breadth of the social identity provides insights into how people engage with an issue such as adoption of new ideas and practices (Crane & Ruebottom 2011, Rowley & Moldoveanu 2003).

al 2008). The lack of consistency in a vast majority of these characteristics in predicting adoption behaviour has led to unstructured adoption and diffusion processes around the globe (Feder & Umali 1993, Mascia & Mills 2018, Ugochukwu & Phillips 2018).

Communication behaviour

Though personality traits and socioeconomic status of individuals are identified as key adoptee traits influencing adoption, diffusion literature on the other hand contends that communication behaviour is critical in determining the spread of innovations and speed of adoption (Banerjee et al 2013, Centola 2015, Jackson & Lopez-Pintado 2013). In many cases, the rate of adoption is dependent on the information sharing patterns and localized interactions between individuals, groups or organisations in social systems (Valente 1996b). Proxies of communication behaviour that influence the spread of innovations are often described in terms of social participation, contact with change agents, cosmopoliteness, exposure to mass media, level of innovation knowledge, and degree of opinion leadership (Boahene et al 1999, Rogers 2010). Although these proxies can provide useful insights on the relationship between communication behaviour and adoption, recent research has stressed the important role of explicitly considering social networks in the diffusion process. Theoretically, social networks[6] captures the notion that individuals are embedded within a larger context of relational ties (Borgatti et al 2009). These networks are often represented by links within or between interacting individuals or groups where ties provides the means by which new information, ideas, and practises can be channelled (Warriner & Moul 1992). Thus, whether and when an individual adopts an innovation is often associated with their

[6] A major contribution to diffusion research has been the categorization of adopters based on network thresholds in the manner described for time of adoption (Rogers 1995, Valente 1996a). The network threshold distribution partition adopter categories such that early adopters are individuals with very low personal network thresholds, i.e., greater than one standard deviation less than the average threshold, whereas later adopters are those with very high network thresholds, i.e., one standard deviation greater than average (Valente 1996a).

individual social network or the proportion of adopters they‘re exposed to (Dearing & Cox 2018, Valente 1996c).

Innovation adoption consequences

Although personality traits, socioeconomic status, and communication channels can predict adoption rates, some studies have demonstrated that changes that occur to an individual as a result of adopting innovations could be the ultimate arbiter in determining whether or not people maintain innovations over time (Foxon & Pearson 2008, Loewe & Dominiquini 2006). In diffusion research, changes that occur to an individual or to a social system as a result of adoption or rejection of an innovation are known as ―innovation adoption consequences" (Rogers 1995, pp 440). Although fundamentally important, the consequences of innovation adoption have received limited attention by diffusion researchers and by change agents (Rogers 1995). However, recent additions to the diffusion of innovations theory stress the need to analyse consequences of innovation adoption (Rogers 2010). This is necessitated by the fact that innovations are highly diverse, adoption rates are highly differential, and innovation adoption consequences cannot be assumed *a priori* (Rogers 1995).

Existing literature that investigates consequences of innovation adoption show that both positive and negative outcomes are possible when people adopt innovations (Brewer et al 2006, Ngoc 2018). In an effort to improve understanding of adoption consequences, it is highly recommended that a long range research approach is needed in which consequences of innovation adoption are analysed as they unfold over time (Rogers 1995). Given that innovation adoption consequences are not unidirectional, scholars initially classified them in a taxonomy as anticipated or unanticipated; desirable or undesirable; direct or indirect (Rogers 1995). However, adjustments to the diffusion of innovations theory have narrowed down the list of categories into two, i.e., public vs. private goods (Rogers 2010). Private goods are benefits associated with one party and not available for others whereas public goods are benefits associated with the entire social system (Wejnert 2002); and 2) benefits vs. costs (Rogers 2010). By analysing both private and public consequences, this all-encompassing simplified approach encapsulates consequences at the individual and community scale.

Conservation diffusion research

Scientists have begun to explore adoption and diffusion of conservation-related interventions (Fuglie & Kascak 2001, Mascia & Mills 2018). A voluminous research literature has accumulated in agricultural systems about variables related to adoption of conservation interventions such as soil tillage practises, sloping agricultural land technologies, integrated pest management technologies, organic farming, among others (Amsalu & De Graaff 2007, Bultena & Hoiberg 1983, Feder et al 1985). An increasing focus is being directed to the factors that promote or constrain adoption.

A series of case studies integrate personality traits such as agency, rationality, risk, in conservation diffusion research (Bélanger & Carter 2008, Horst et al 2007). In some cases, personal attributes have been shown to outweigh sector specific issues and priorities in the innovation adoption processes. Factors such as risk and risk aversion have been related to the rate of adoption of modern conservation technologies by farmers in different regions (Feder 1980). For example, risk aversion can be a key constraint to the rapid adoption of agricultural land conservation technologies (Fisher et al 2018, Guerin & Guerin 1994, Knowler & Bradshaw 2007). A study by Fernandez-Cornejo et al (1996) showed that farmers that were willing to take risks were more likely to be early adopters of integrated pest management technologies among vegetable growers in Florida. However, other research has argued that because personal attributes revolve around perceptions, a positive perception based on a given personality attribute may not always translate to a positive intent to adopt novel conservation interventions (Adesina & Zinnah 1993, Greiner & Gregg 2011). Thus, there is a need to examine the impact of personal attributes in relation to other socioeconomic and demographic factors that may exist in the social system (Feder 1980).

Much of the conservation adoption literature, particularly in agricultural systems has focused on socioeconomic and demographic factors associated with farms and farmers, such as farm size, access to credit, income, education, age, access to extension services, and ownership of productive assets (Brush et al 1992, Bultena & Hoiberg 1983, Greiner & Gregg 2011, Jung & Kim 2017). For example, several studies have found that education has a positive impact on adoption of soil conservation technologies and other natural resource management schemes (D'Souza & Mishra 2018, Feder et al 1985, Mwangi & Kariuki 2015), whereas farm size can have a positive influence on the adoption of a number of conservation farming technologies (Knowler & Bradshaw 2007, Mercer 2004). Younger farmers have been found to be educated and more involved with more innovative farming (Feder & Umali 1993), while older farmers with shorter planning horizons tend to be less receptive to soil conservation practices (Jung & Kim 2017, Norris & Batie 1987). Income can have a positive influence on adoption of erosion control practices (Feder & Umali 1993, Jung & Kim 2017). It is generally held that renters of productive assets such as farmland are less likely to invest in conservation practices; although, other studies found that renters can rapidly embrace the use conservation tillage than full owners (Lee & Stewart 1983).

Depending on stage of the diffusion process, some socioeconomic factors that influence adoption can be more or less important (Barham et al 2004, Feder & Umali 1993, Läpple & Van Rensburg 2011). For example, a study that examined the determinants of adoption of sloping agricultural land technologies in the Philippines show that farm size, ownership of productive assets, education, access to extension services, and access to credit were major determinants of the speed of adoption by various users during the early phases of adoption (Feder et al 1985). However, subsequent surveys at a phase when the technology had reached the final stage of the diffusion process indicated that the impact of many of these factors to be no longer significant (Feder & Umali 1993). Precisely, factors such as ownership of productive assets, age, education, and farm size were not significant determinants of adoption during the later stages of the diffusion process (David & Otsuka 1990, Ramasamy et al 1992, Upadhyaya et al 1993).

In terms of communication behaviour, adopters of conservation practises have been characterized to have strong social ties with other adopters (Pannell et al 2006a, Tenge et al 2004). This reflects a form of social influence among potential adopters (Valente 1996b). Others studies that integrate proxies of communication behaviour in adoption and diffusion processes have shown that adopters of soil and water conservation measures tend to be more integrated in the social community and have intensive contact with information and extension services (Amsalu & De Graaff 2007, De Graaff et al 2008).

Key knowledge gaps in conservation diffusion research

The topic of conservation diffusion is gaining momentum in the literature; however, most studies do not follow the classical diffusion models developed over the years in diffusion research (Rogers 2010, Valente 1996c). Foremost, most conservation diffusion studies are mainly based on a comparison between adopters and non-adopters (Bultena & Hoiberg 1983, Burton et al 2003, Dadi et al 2004, Sheikh et al 2003). Yet, classical diffusion studies contend that, at a minimum, there should be four important categories of adoption behaviour: early adopters, late adopters, non-adopters, and one that is often overlooked dis-adopters (those that adopt but later quit) (Barham et al 2004, D'Souza & Mishra 2018). Distinction between groups is important because early and late adopters respond differently to economic and non-economic factors when they consider whether or not to adopt novel interventions (Rogers 2010).

Early adopters are key to any diffusion process because they often provide initial practical evidence that an intervention actually works – a critical element in any diffusion process (Rogers 2003). Moreover, early adopters provide the critical mass[7] needed to accelerate any diffusion process (Valente 1996b). The importance of late adopters is that they provide wider legitimacy, credibility, saliency, and confirmation to others that the intervention is beneficial over time (Rogers 2010). Depending on the reasons associated with dis-adoption, this situation can potentially undermine conservation diffusion processes over time (Barham et al 2004, Guerin & Guerin 1994). It is often argued that dis-adopters can potentially slow down or even reverse diffusion processes depending on their position and capacity in the social system (D'Souza & Mishra 2018, Dinar & Yaron 2002). Although differences among the four groups are well acknowledged in the extant diffusion literature (Dearing & Cox 2018, Fuglie & Kascak 2001, Rogers 2010, Ryan & Gross 1943), very few empirical studies have explored factors that influence dis-adoption or the differences in the factors that affect dis-adoption, adoption, and non-adoption of conservation interventions over time.

Another grey area in conservation diffusion literature is the lack of a specific framework to identify intermediaries to facilitate conservation transfer through target populations. Like many innovations, conservation strategies often originate from external actors (Arias 2015). Given the increase in scope and magnitude of environmental issues, matched by equally complex social settings, conservation interventions may not always be framed in a format that can be easily understood by target populations (Hughes et al 2017, Kirchhoff et al 2013). In such cases, intermediaries are often needed to bridge these information and knowledge gaps between higher-level institutional actors and local target communities (Berkes 2009). Indeed, barriers of knowledge exchange between technical actors with global perspectives on

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[7] Critical mass refers to a system level measure of the minimum number of participants needed to sustain a diffusion process (Valente 1996a).

resource conservation and those that operate within localized arrangements have been cited as major constraints of conservation diffusion (Nguyen et al 2017).

To date, natural resource managers and conservation practitioners have consistently relied on local community leaders to diffuse and implement conservation actions at the community level (Armitage et al 2008, McClanahan & Cinner 2008, Olsson et al 2004). Such approaches have wide appeal to managers because formal leaders are easily identified and leadership characteristics are known to be important for the initiation and maintenance of many environmental conservation and management initiatives (Olsson et al 2004, Ostrom 2007b, Pretty 2003). Yet while these leaders may truly be better positioned to implement certain conservation and management actions, they are not always the most effective at diffusing and spearheading all types of conservation initiatives (Barnes-Mauthe et al 2015), and in some cases may struggle to deliver greater than localized conservation outcomes (Berkes 2004, Pajaro et al 2010). Due to a lack of understanding of the complexity, sociocultural diversity and dynamic nature of diverse social structures embedded within social-ecological systems, even relatively simple, low cost conservation initiatives can suffer from poor rates of success (Barnes-Mauthe et al 2015, Mertens et al 2005). At worst, they can result in conflicts (Ban et al 2013, Cohen et al 2012, Cumming et al 2006). Therefore, there is a need to develop criteria for stakeholder identification that is context specific that will enable conservation practitioners better implement conservation.

Conservation tends to alter existing socio-economic arrangements with some degree of uncertainty (Mascia et al 2010, Milner-Gulland et al 2014). However, many conservation programs do not analyse the consequential effects of conservation adoption or non-adoption on people. Arguments for this narrative have pointed to either sponsors of conservation research who overemphasize adoption per se, or the inappropriateness of survey methods to investigate consequences (Dudley & Stolton 2010, Gurney et al 2015). In other cases, conservation practitioners may simply assume that conservation produces desirable outcomes for those who adopt (Cooke et al 2017, Cumming 2018, Lundquist & Granek 2005). Yet, existing literature that investigate relationships between people and nature, particularly on the implications of natural resource management strategies show that conservation can have both positive and/or negative outcomes on the environment and associated human communities (Ferraro & Hanauer 2014, Gurney et al 2014, Scherr 2000). Indeed, understanding the crucial linkage between adoption or non-adoption of conservation and changes to both people‘s wellbeing and the environment can help in formulating environmental policies that contribute to sustainability (Coulthard 2012, Weeratunge et al 2014).

Research gaps

Against this background, four broad knowledge gaps emerge: (i) unclear understanding of factors that influence adoption and diffusion of conservation interventions over time, (2) lack of a specific criteria to identify intermediaries to facilitate conservation transfer through target populations, (3) poor understanding of the consequences (i.e. impacts) of conservation diffusion on people, (4) little understanding of the consequences (i.e. impacts) of conservation diffusion on environment.

Gap 1: Limited studies have examined the effect of social networks on conservation diffusion process

To understand what causes or constrains conservation diffusion, several studies have examined the influence of various determinants on adoption decisions. However, a vast amount of this literature is mainly based on the influence of personality traits and socioeconomic status on conservation adoption decisions (Amsalu & De Graaff 2007, Bultena & Hoiberg 1983, Padgett 2011, Tiwari et al 2008). Chapter 2 has an extended review of personality and socioeconomic characteristics that have been empirically tested to influence conservation adoption behaviour in natural resource management context. Conversely, there remains very limited work emphasizing the effect of social networks on conservation diffusion. Although the word ‗social network' is extensively used in the development economics literature (e.g., Barr & Fafchamps 2010, Ductor et al 2014, Fafchamps & Gubert 2007, Udry & Conley 2004), none of these studies empirically measured social networks in a conventional way that would allow the use of standard social network analysis tools. The vast majority of these studies tend to focus on kinship ties rather than the traditional ego networks where a sample of participants report their personal egonets and their associated individual attributes (Robins 2015).

Although a few studies have provided some considerations to ways of up scaling conservation based on network processes (Matous & Todo 2015, Pietri et al 2009), no specifics as to the structure and function of the social network are given. Only a few studies provide the general rationale with regards to the role of the social networks in conservation diffusion process by defining key network structures that can be harnessed to facilitate diffusion (Bodin & Crona 2009, Cohen et al 2012, Ramirez-Sanchez 2011a). However, these studies are mostly limited to diffusion of conservation information, yet conservation interventions can be incredibly diverse ranging from information-based conservation strategies to complex initiatives that seek behaviour change (Genius et al 2006, Sanchirico & Emerson 2002). One of the few attempts to empirically test the influence of networks on adoption of conservation is a study by Warriner and Moul, (1992). The authors explore the influence of personal communication networks on adoption of conservation tillage practises among crop farmers in Ontario, Canada. Although their results revealed a positive influence of network connectedness on adoption, their analysis relied only on one network attribute based on number of direct ties (i.e., actor direct connectedness) rather than structural characteristics of the network itself. Furthermore, their analysis was cross-sectional and based on regression frameworks that are often considered inappropriate for modelling network data (Robins 2015).

To date, a critical research gap is that few empirical studies have explored the role of social networks on the adoption and diffusion of conservation interventions over time. Here, I address this gap by modelling conservation adoption patterns over time based on individuals' social networks while taking account of personality traits and socioeconomic status attributes. Unlike previous research, here I simultaneously test the effect of key socioeconomic factors that have been empirically shown to influence adoption behaviour (see chapter 2), and network effects that have been widely used to model behaviour in social networks (Lusher et al 2013, Wang et al 2014). By utilizing the social network approach, this thesis moves beyond the conventional analysis of adoption behaviour to a more refined and robust approach that specifies further the relational basis of adoption. To capture differences among all possible adopter categories in any diffusion process, this thesis presents a robust comparison based on early, late, non-adopters, and dis-adopters.

Gap 2: No specific criteria exist for selecting key stakeholders to facilitate more widespread adoption and diffusion of conservation interventions

In many cases, conservation agendas tend to originate from top experts such as government officials, state, regional authorities, and technical experts (Arias 2015). Once firmly established, implementation of conservation is then directed to target populations. Owing to this approach, implementation of conservation tends to follow the top down centralized diffusion system[8] (Rogers 2004). As such, proper communication channels are clearly needed to facilitate conservation transfer. This step requires proper identification of intermediaries

[8] Centralized diffusion systems are based on a more linear, one-way model of communication, i.e., innovations originate from a centralized source such as government administrators and technical subject matter experts and then diffuse to users (Rogers 1995).

who can serve varied functions between authorities, experts, and local resource users (Borgatti 2006). The functions might include linking potential adopters with experts, and facilitating the flow of ideas and practises between developers of the conservation agenda and local users (Prell et al 2009, Reed et al 2009).

One of the major challenges in conservation diffusion is the identification of the right stakeholders to engage with to facilitate adoption and diffusion of conservation interventions through target populations. Moreover, conservation diffusion goals can be incredibly diverse. For example, spreading of conservation information quickly is often necessary, especially when rapid awareness creation is needed to protect and safeguard certain species or habitats under emergency threat (Haddow et al 2013, Kapucu 2008). Where social systems are comprised of disjointed social structures, there is often a need to bridge conservation ideas and practises amongst disconnected groups (Barnes et al 2016). In cases where conservation initiatives specifically seek to implement behaviour change among various stakeholders, multiple direct contacts and persistence would be needed to influence adoption (Christie 2000). Spreading conservation information widely and facilitating widespread adoption of more complex conservation initiatives over a longer time period is often necessary to achieve global sustainability outcomes (Mace 2014, Pannell et al 2006b).

To successfully achieve the distinct diffusion related conservation objectives, different types of stakeholders may be more important to involve depending on the specific conservation diffusion goal. However, despite the diversity of goals associated with conservation initiatives, no criteria exist for selecting key stakeholders ideally placed to successfully implement the distinct diffusion-related conservation objectives. This lack of specific guidelines for selecting individuals most ideally placed to facilitate conservation diffusion is a critical research gap in conservation diffusion processes addressed in this thesis. This gap is addressed by presenting specific criteria for identifying stakeholders that are optimally positioned to diffuse conservation information, knowledge, and practices that can be fundamental to successful conservation efforts in natural resource management systems (Armitage et al 2008, Ostrom 2007b).

Gap 3: Little understanding of the impact of conservation diffusion on people

Beyond ecosystems, there has been numerous calls for putting associated human communities at the centre of impact evaluation studies in the nature conservation context (Gough & McGregor 2007, MEA 2005). These calls are underscored by empirical evidence that shows severe negative impacts of conservation interventions on some domains of people‘s wellbeing (Beauchamp et al 2018b, MEA 2005). The inclusion of wellbeing in the conservation discourse is further driven by the notion that without meeting the needs and gaining the support of the people that conservation interventions affect, those interventions will inevitably fail (de Lange et al 2016). Indeed, there is an increased consensus among international policy circles that conservation should at very least do no harm to the local populations affected by interventions (Biedenweg & Gross-Camp 2018).

Apart from the paucity of studies that analyse the effects of conservation on people, other concerns are raised on the indicators used to capture people‘s wellbeing. Existing impact evaluation studies in the natural resource management context are predominantly based on monetary or material measures (Charles et al 2015, Cochrane 2000). Measures that are often considered narrow, incomplete, and misleading because they do not reflect anything more than just the material dimension of peoples wellbeing (Weeratunge et al 2014). Yet, people‘s perceptions about quality of life and pursuit of happiness also matter to wellbeing (Abunge et al 2013, Ban et al 2013, Coulthard et al 2011). For example, investigations that pay deeper attention to the impacts of conservation such as marine protected areas (MPAs) on people reveal that conservation can result in substantial alterations to people‘s way of life and general wellbeing (Ban et al 2013, Coulthard et al 2014, Pullin et al 2013). As a result, several reviews on environmental impact assessment research have proposed other multi-dimensional wellbeing concepts and indicators that take into account social and subjective dimensions of people‘s wellbeing (Camfield et al 2009b, McGregor et al 2009).

Despite the diversity of opinions on how wellbeing is conceptualized, consensus is forming that wellbeing is multidimensional, and composed of both objective and subjective components (Gough & McGregor 2007). These components are guided through three key dimensions, i.e., material, relational, and subjective dimensions (Gough & McGregor 2007, Narayan-Parker 2000). Material wellbeing refers to the material conditions of life (Gough & McGregor 2007). These conditions subsumes finance or income, quality of the living environment, and possessions (White 2010). Perceptions about the broader notion of quality of life as well as meanings and experiences related to competence, autonomy, and identity falls within the dimensions of subjective wellbeing (McGregor 2007). Taking a broad view on interconnectedness, social ties and relationships that link people together are considered key determinants of relational wellbeing (Camfield et al 2009a). Considering and understanding impacts of conservation interventions on material, relational, and subjective dimensions of wellbeing matters for a number of reasons. Firstly, conservation project implementers are morally responsible for ensuring that conservation interventions do not undermine the economic progress of local communities (Hutton et al 2005). Secondly, negative impacts on subjective wellbeing can potentially erode local support and therefore jeopardize environmental outcomes (Woodhouse et al 2015). Thirdly, the interplay between people and their relational circumstances can explicitly determine their scope for personal and collective action to safeguard a common resource (Charles et al 2012). In sum, the wellbeing indicators not only provides a more comprehensive way to look at conservation outcomes on people, but they represent an analytical lens which can help draw policy attention to the nonmaterial outcomes of conservation. This effectively adds value to our understanding of social and subjective implications of conservation in social-ecological systems (Coulthard 2012, Weeratunge et al 2014).

Despite the emerging recognition on the robustness of the alternative indicators in impact assessments research in natural resource management context, no impact evaluation study has compared multi-dimensional wellbeing concepts between adopters and non-adopters of conservation initiatives. The lack of robust investigations of the impacts of conservation on people is a considerable knowledge gap addressed in this thesis. This thesis addresses this key research gap by applying multi-dimensional approaches to understand the objective and subjective impacts of conservation. Precisely, this thesis emphasizes key components of material, relational, and subjective dimensions of wellbeing, each of which being relevant to human wellbeing at the individual scale (Coulthard et al 2011, McGregor & Sumner 2010). Understanding the crucial linkage between adoption or non-adoption of conservation and changes in people can help in formulating environmental policies that contribute to human wellbeing (Coulthard 2012, Weeratunge et al 2014).

Gap 4: Linkages between use of conservation-friendly fishing technologies and assemblage functioning is still unclear

Linkages between conservation and the environment has always been an important component of natural resource management (Pitcher 2001, Pitcher & Pauly 1998). Understanding the ecosystem impacts of conservation therefore remains critical particularly in the context of anticipated change (Hughes et al 2017). Studies that analyse impacts of conservation on the environment affirm that certain interventions can be either beneficial and/or detrimental to the environment (Eklöf et al 2009, Hannah & Jones 2007, Weeks et al

2010). For example, despite the overwhelming publicity about the effectiveness of marine protected areas (MPAs) in biodiversity protection, a series of studies have demonstrated some degree of MPAs‘ ineffectiveness as solutions to biodiversity erosion in the marine environment (Benjamin 2003, Eklöf et al 2009, Mascia et al 2010, Pauly et al 2002, Weeks et al 2010). Similarly, fisheries conservation interventions such as gear restrictions, bycatch reduction devices, mesh size regulations are often enforced to protect certain sizes and species of fish (McClanahan 2010). However, empirical evidence now exists that shows a vast majority of gear-based management interventions tend to have little effect on conservation gains such as increasing fish biomass compared to other forms of management e.g., marine reserves (Cinner et al 2016, Cinner et al 2018, MacNeil et al 2015).

In marine ecosystems, fishing remains one of the major drivers of change worldwide (Worm et al 2006). A primary focus of the global marine conservation agenda has been gear or technology-based interventions intended to reduce negative spillovers or environmental externalities associated with resource extraction (McClanahan 2010). One such fisheries gear-based conservation intervention, i.e. the escape slot trap, was introduced in Africa and globally in order to catch species of fish at sizes that do not undermine sustainability (Gomes et al 2014, Johnson 2010). This is a modified basket trap retrofitted with escape gaps that allows juveniles and narrow-bodied, low value fish species (i.e. bycatch) to exit, while larger, wider-bodied target species are retained (Mbaru & McClanahan 2013).

Although escape slots can be effective in reducing catch of juveniles and narrow-bodied species (i.e. bycatch) (Gomes et al 2014, Johnson 2010, Mbaru & McClanahan 2013), no study has examined the functional diversity that these traps may remove from the ecosystem. Yet, the growing interest in an ecosystem-based approach has stressed maintaining and sustaining ecological functions (Sinclair et al 2002, Tillin et al 2006). Indeed, examining the relationship between fishing and ecological function is key to understanding the effect of fishing on marine ecosystems (Koutsidi et al 2016, Micheli et al 2014). This thesis therefore integrates emerging frameworks in functional ecology (Mouillot et al 2014) to investigate the functions that escape slot traps may remove from the ecosystem. To determine the potential for escape slot traps to have an ecological impact, I quantify overlaps in catch composition between escape slot traps and other gear types that operate concurrently in the same reefs.

Study objectives and thesis structure

The overall objectives of this study are to examine how people adopt conservation innovations, and determine key social and environmental impacts of doing so. These objectives will be addressed by answering the following research questions:

1. What factors determine the uptake (adoption) and spread (diffusion) of conservation interventions over time? (Chapter 3)
2. Who are the key stakeholders to engage with when rolling out conservation programs? (Chapter 4)
3. How does adoption of conservation initiatives affect people's wellbeing? (Chapter 5)
4. How does adoption of conservation initiatives affect the ecosystem? (Chapter 6)

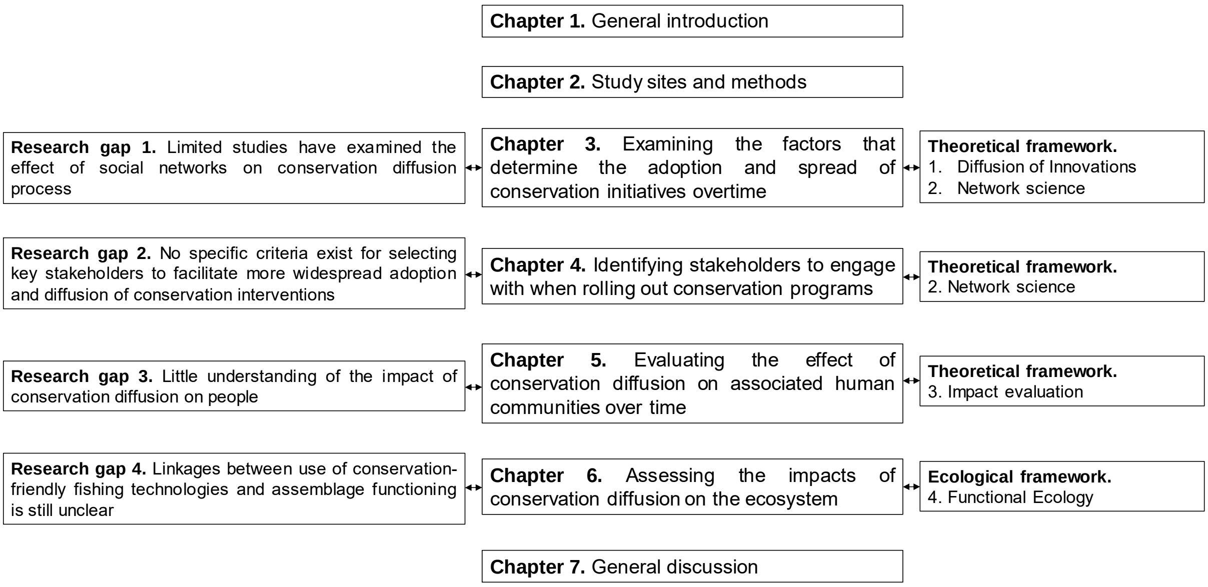

Figure 2. Thesis structure, research gaps addressed and theoretical frameworks of thesis chapters.

Thesis chapters

Chapter 3: What factors determine the uptake (adoption) and spread (diffusion) of conservation initiatives over time? In this chapter, I integrate decades of social science theory on diffusion of innovation with novel breakthroughs in social network science to offer a clearer understanding of the factors that shape adoption behaviour patterns of conservation initiatives over time.

Chapter 4: Who are the key stakeholders to engage with when rolling out conservation programs? Here, I draw on social network theory and methods to develop specific criteria for selecting key stakeholders to facilitate diffusion of conservation information, as well complex knowledge or complex conservation initiatives that specifically target behaviour change.

Chapter 5: How does adoption of conservation initiatives affect people‘s wellbeing? To evaluate the impact of conservation initiatives on people overtime, I draw insights from the wellbeing framework (material, subjective, relational). The wellbeing framework is explicitly viewed as a robust tool to bridge the gap between natural resource sustainability and socioeconomic development, a fundamental aspect in policy processes (Coulthard et al 2011). Indeed, policies for ecological sustainability of natural resources are more likely to succeed when they draw on insights from a wellbeing perspective (Ban et al 2013).

Chapter 6: How does adoption of conservation initiatives affect the ecosystem? Here, I employ a trait-based approach to determine whether marine conservation technologies (specifically gear-based management) are associated with certain traits, potentially affecting assemblage functioning (Mouillot et al 2014). This analysis attempts to connect traits to fishing gears in multi-species coral reef fisheries and provide insights on how fishing affect assemblage functioning in tropical coral reef fisheries. The linkages between use of specific fishing gears and the targeting of ecosystem functions are particularly important for the many multi-species fisheries in vulnerable ecosystems.

Chapter 2: Study sites and methods

Contextual background of the Kenyan marine fishery

The Kenyan coastal fishery is predominantly small-scale and artisanal (Daw et al 2009). Local fishers operate within a narrow continental shelf between 2.5 to 3.0 nautical miles (McClanahan & Mangi 2004). Despite operating within a small strip, the fishery supports more than 23,000 fishers catching over 16,000 tonnes of fish annually (McClanahan & Mangi 2004). The subsector also provides monetary income and animal protein to about 70% of the coastal communities (Glaesel 1997, Tuda et al 2008). Over the years, the local fishery has however grappled with a number of management challenges. Some of the major problems facing the fishery include the rise in the number of small-scale fishers (Ochiewo 2004), excessive and destructive fishing (McClanahan et al 2008).

To address these challenges, Kenya has prioritized a number of measures to conserve and manage her natural resources; these include the establishment of marine protected areas (MPAs) and beach management units (BMUs) to delegate responsibility to stakeholders to administer their natural resources at the local level (McClanahan & Mangi 2004). More recently, Kenya has also implemented gear-based management approaches by eliminating beach seines responsible for catching very small fish (McClanahan 2010), while promoting gears that catch most of the available species at sizes that do not undermine sustainability (McClanahan & Mangi 2004), e.g. the escape slot trap (Condy et al 2014). These modified traps are expected to increase size selectivity by reducing the catch of juveniles and narrow-bodied species without compromising the fisherman‘s income (Mbaru & McClanahan 2013). Periodic patrols are also maintained to check illegal, unreported and unregulated fishing (Athawale 2012).

Gear utilization

Eleven different gear types are commonly used in this coastal fishery both on the reef and even beyond the reef (Mangi & Roberts 2006, Mbaru 2012). These include basket traps, gillnets, spearguns, hook and lines, beach seines, longlines, trolling, ringnets, castnets, fence traps and scoop nets. Basket traps are the most dominant accounting for about 40% of the total fishing effort (Mbaru & McClanahan 2013). These traps are popular because they retain most fish that enter (Munro 1983). By retaining a vast majority of the fish caught, basket trap fishing often results in a catch with a high species composition (Johnson 2010; Fig. 3a). Only a small proportion of fishers use gears such as hook and lines that target pelagic stocks (Mbaru 2012). The lack of adequate equipment such as boats and engines has limited the use of offshore fishing nets such as ring nets and large mesh sized gillnets (Mbaru 2012). Many of the gear types used within the reef (e.g., basket trap, hook and line, speargun, gillnet, beach seine) are commonly used in small-scale coral reef fisheries around the world (Cinner et al 2009b).

Institutional management framework

Various stakeholders are involved in the management of the Kenya marine fishery (McClanahan et al 2011). The Fisheries Act (Cap 378 of the Laws of Kenya) gives the State Department of Fisheries (SDF) mandate to explore, exploit, utilize, manage, develop, and conserve fishery resources. Research on the fisheries resources is a function of the Kenya Marine and Fisheries Research Institute (KMFRI). The Wildlife (Conservation) Act (Cap 376) recognizes Kenya Wildlife Service (KWS) as the agency responsible for conservation and management of Marine Protected Areas (MPAs). Apart from the state owned agencies, other non-governmental organizations (NGOs) are also licensed to conduct marine research along the Kenyan coast.

The Kenyan coastline also falls under the jurisdiction of various local county governments (Gomes et al 2014). Matters of environmental sustainability, human development capacity and empowerment, marketing of fish and other marine related products are addressed by the local county authorities (Gomes et al 2014). Since 2006, the SDF introduced community based management (co-management) where fishers were organized into beach management units (BMUs). This decentralized approach allowed for multi-stakeholder co-management of natural resources with the SDF in specific geographic locations (typically including one or more fish landing sites) at the local level (Cinner et al 2009c). Within their area of jurisdiction, BMUs are required to develop their own bylaws, e.g., they can restrict space, time, gear, species, and life history stages of fish being caught, or establish a no take fishery closure (Cinner et al 2009c).

The escape slot trap

Fish traps capture a significant portion of the reef fish both in Africa and globally (Johnson 2010, Mbaru & McClanahan 2013, Munro 1983). High-value fish such as rabbitfishes, groupers (siganidae, serranidae) and snappers (lutjanidae) are typical targets of trap fishers (Mbaru & McClanahan 2013). However, traps also tend to harvest a vast majority of non-target species such as butterfly fishes (chaetodontidae), box fishes (ostraciidae), including high bycatch of key herbivores parrotfish (scaridae) and surgeonfish (Acanthuridae) (Johnson 2010). Consequently, many small-scale coastal fisheries can be stripped of their resources if the trap fishery remains unregulated.

Over the years, management of trap fisheries had focused almost exclusively on the use of larger mesh sizes to reduce the catch of juveniles (Laarman & Ryckman 1982, Mahon & Hunte 2001, Olsen et al 1978). However, given the diverse morphologies of fish caught by traps, selecting one mesh size that optimizes the yield of all exploited species has been a major challenge (Laarman & Ryckman 1982, Mahon & Hunte 2001, Olsen et al 1978). For example, aside from releasing low-value and narrow-bodied fish (e.g., butterflyfish), large mesh would also permit escape of high-value target species (e.g., groupers) (Bohnsack et al 1989). Indeed, (Johnson 2010) showed that hexagonal mesh with 5 x 8 cm aperture reduced the mean number of fish caught and the mean catch value compared to a normal basket trap. An alternative and more effective solution to the problem of bycatch in fish traps has been the introduction of escape slots (Fig. 3b).

Initial experiments with escape slots were carried out in the Antillean crab fisheries to allow mainly non-targeted finfish to escape through the slots in lobster traps (Munro 1974). Later, the same technology was introduced in the Caribbean coral reef trap fin fisheries to allow juveniles and narrow-bodied, low-value species exit (Gobert 1994, Johnson 2010, Mahon & Hunte 2001). Currently, several African coastal states including Kenya, Tanzania, and Mozambique have begun to adopt these modified traps in an effort to protect certain sizes and species of fish in the dominant basket trap fishery (McClanahan & Kosgei 2018).

Escape slots allows juveniles, low value and narrow-bodied species to exit, while retaining high value target species (Fig. 3b). Reducing the catch of juveniles (i.e., reproductively immature fish) can increase long-term sustainability of the fishery by allowing fish to grow and reproduce before they are caught (Thomsen et al 2011). Many narrow-bodied, ornamental species are rarely targeted by fishers because they are undesirable as food (Johnson 2010). Importantly, ornamental species can promote ecotourism in these villages and fishing grounds (Parsons & Thur 2008, Suuronen et al 2012). By retaining high value target species (i.e., groupers, snappers, emperors, rabbitfish), profitability is maintained (Gomes et al 2014). The inclusion of escape slots can potentially reduce catch of key herbivores (e.g., parrotfish and surgeonfish) who help maintain the coral dominance on reefs by up to 58% (Mbaru & McClanahan 2013). This means that using escape slot traps can sustain the population of critical algal grazers that suppress the dominance of algae in coral reef ecosystems (Hughes et al 2007). Thus, despite the diversity of fish caught with traps, escape slot can provide a long-term solution to the adverse ecological impacts associated with trap fishing. No specialized training is required on the part of basket trap fishers in fabricating and deployment during transition from using basket traps to escape slot traps. This therefore makes the technology more adaptable and inexpensive (Mbaru & McClanahan 2013).

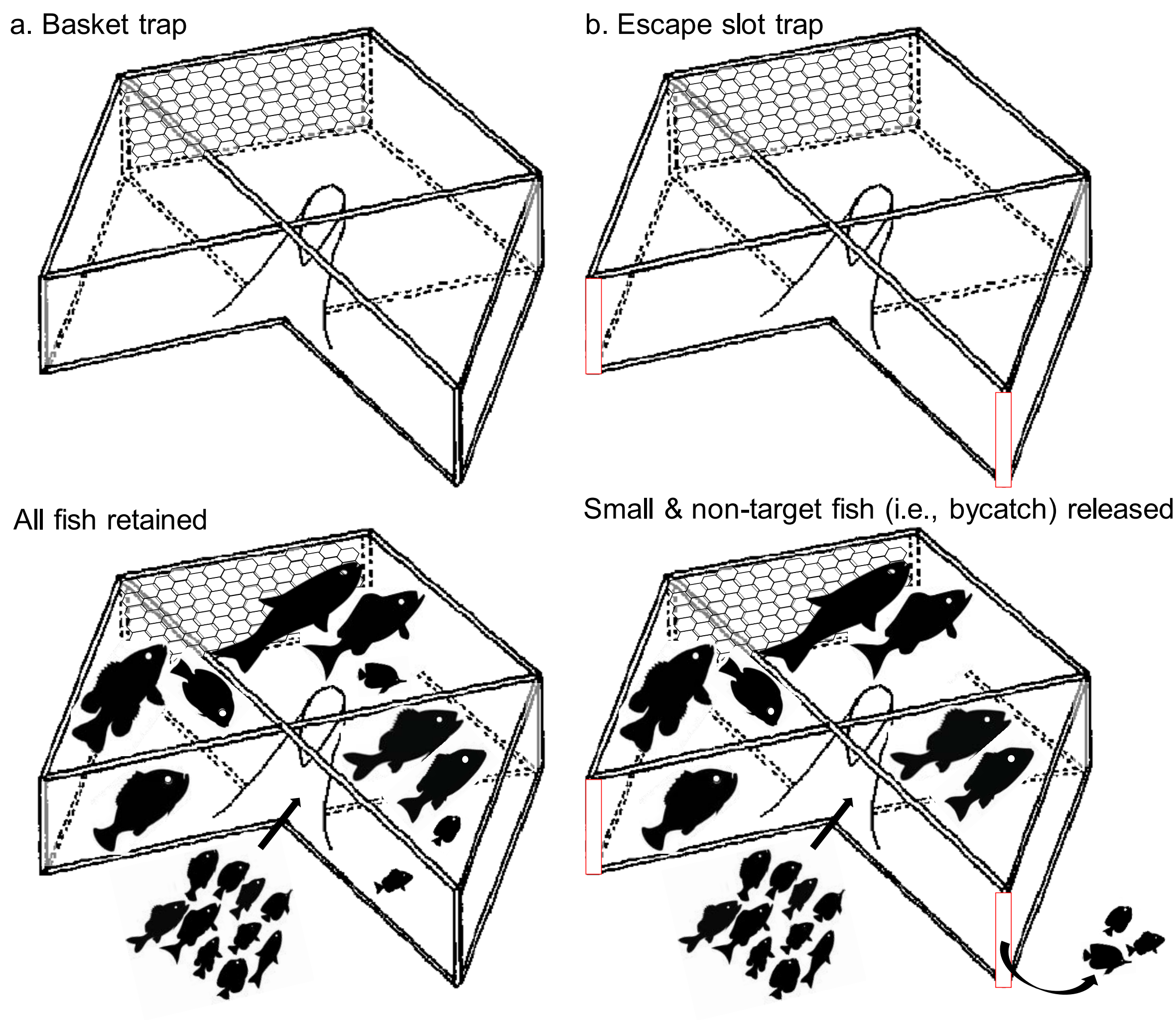

Figure 3. A heuristic representation of the conservation intervention, i.e., escape slot fishing trap. Diagrams illustrate structural and operational differences between the unmodified basket trap and escape slot trap.

Research setting, survey design, and data collection

This research was conducted in six major fishing landing sites along the Kenyan coast (Fig. 4). I focused my primary data collection on study sites where traps represented the dominant fishing gear in use. Within the six fish landing sites surveyed, two were controls (i.e., where the conservation intervention was never introduced). In chapters 3, 4, and 5, I will use different combinations of data collected to address the relevant research objective, which will be specifically detailed in the methods sections of each chapter. The target population was therefore defined as active trap fishers (preferable fishing captains) because existing research in the region indicates that captains bear ultimate responsibility for all actions and decisions about fishing (McClanahan et al 2012). A total of 265 trap fishers (hereinafter ‗respondents') were interviewed, representing over 95% of the target population at each of the six villages. Precisely, I surveyed 34 respondents in site A, 59 in site B, 49 in site C, 36 in site D, 45 in site E, and 42 in site F. In the experimental sites, a fisher is considered an adopter if s/he fabricates an escape slot trap or modifies at least one existing trap by introducing the escape slots. Fishers who never used escape slot traps during the survey period were classified as non-adopters. Dis-adopters are fishers that adopted the intervention, but later abandoned it. A total of 62 fishers were given the new gear to conduct experimental fishing. However, for the purposes of this study, they were not considered adopters unless they modified their own traps.

Panel data study

The study was coupled with the conservation intervention to track the diffusion process through time. This research therefore makes use of panel data comprising responses to the same questions by the same participants over three-time period. Panel data is considered gold standard in social science because the same individual is tracked overtime, which allows multiple sources of variance to be held constant (Bell & Jones 2015, Lohse et al 2000).

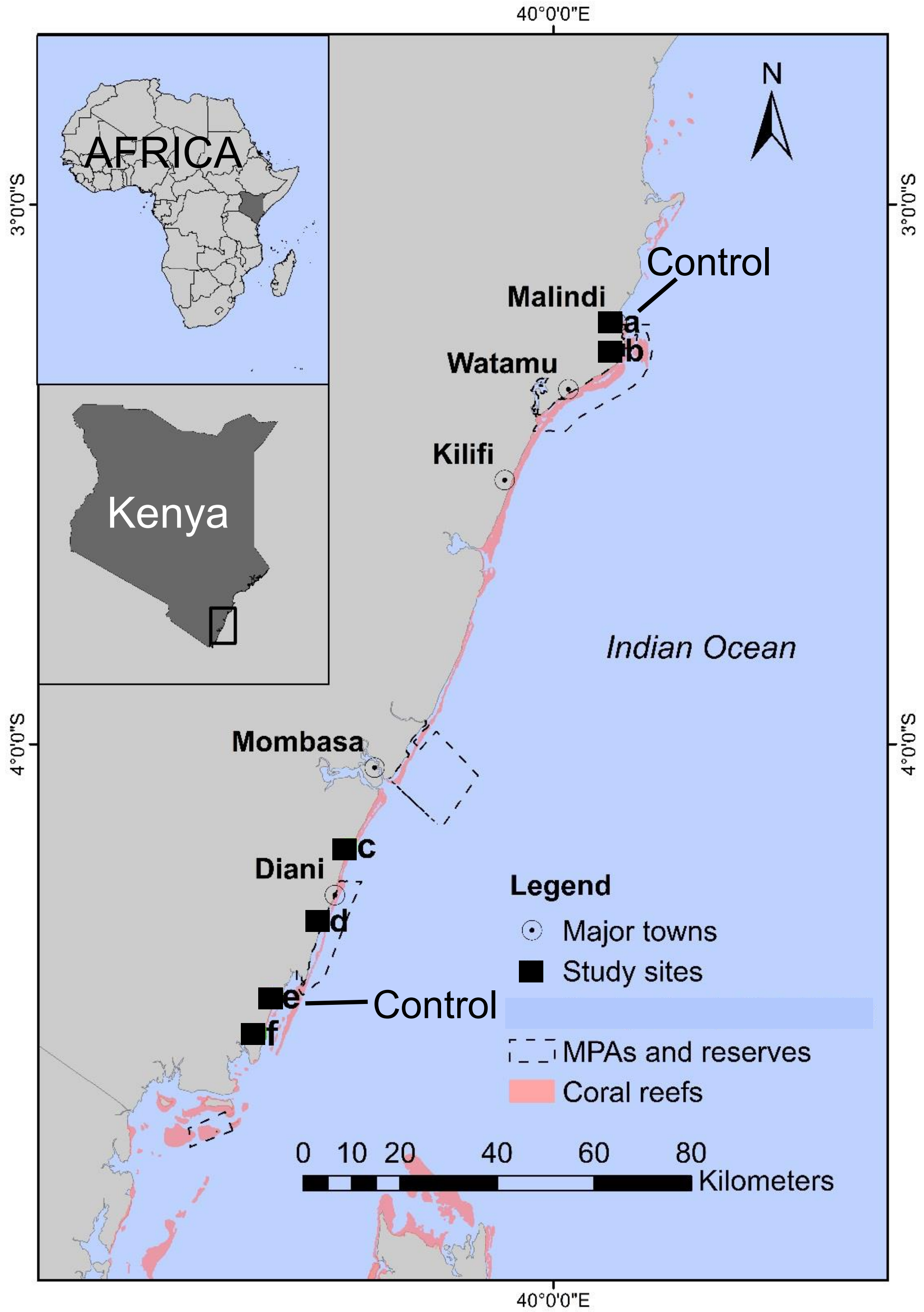

Figure 4. Map showing study sites. Boundaries of Marine Protected Areas (MPAs) and marine reserves are shown as dashed lines. Site a and e are control sites where escape slot traps were not introduced.

Panel data is sometimes associated with attrition bias (loss of panel members overtime), panel selection bias (when people surveyed are different from the population), and conditioning effects. Conditioning effects happen when the process of conducting surveys affect its findings (Lohse et al 2000). For example, when people are asked regularly whether they intend to adopt a product may come to the conclusion that they should develop such innovation (Kinnear &Taylor 1996). Here, panel attrition was almost negligible because only a few fishers (15/265) were surveyed in one time period during the project implementation phase. I addressed panel selection bias by sampling over 95% of the target population at each of the six villages. A one year interval between surveys was considered wide enough to minimise any conditional effects. Precisely, I used panel data in two aspects of this thesis: first, to look at dynamic networks in chapter 3, and second, to look at whether individuals who adopted the escape slot trap had different wealth measures, subjective wellbeing outcomes, and levels of reciprocity from individuals who did not (chapter 5).

Table 1. Thesis chapters, research objectives, and type of data used.

Thesis chapter	Research objective	Panel data
Chapter 3	Determine the factors that influence uptake (adoption) and spread (diffusion) of a conservation intervention over time.	Used
Chapter 4	Identify key stakeholders to facilitate conservation transfer.	Not used
Chapter 5	Investigate impacts of conservation diffusion on people"s wellbeing.	Used
Chapter 6	Examine impacts of conservation diffusion on the ecosystem.	Not used

Prior to the launch of the project, I conducted baseline surveys. Two follow-up surveys were conducted at an interval of one year each after the conservation program rolled out the innovation. Data was collected using questionnaires administered through face-to-face interviews conducted in Swahili. Chapter 6 differs from the other chapters in that it uses a dataset on coral reef fisheries landings from 25 sites across Kenya over a seven-year period

(Table 1). The catch data include creel surveys conducted annually between 2010 and 2016. Of the 25 sites included in this chapter, four sites overlap with the other chapters (Fig. 5).

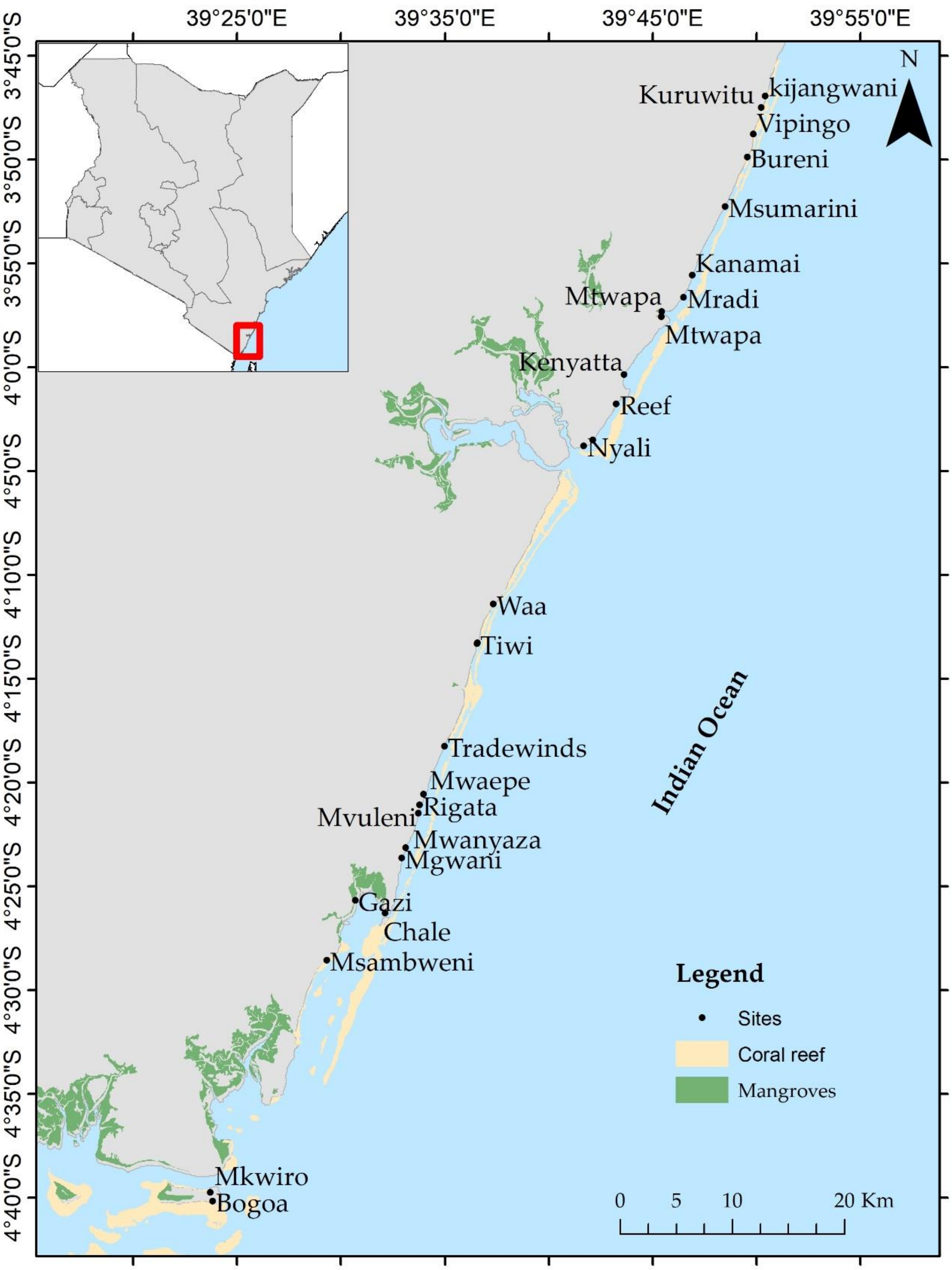

Figure 5. Catch sampling sites for fish data used in chapter 6.

Review of predictor and control variables

This review covers predictor variables used to address research objectives for chapter 3, 4, and 5 as well as control variables used in chapter 5. A review of empirical diffusion studies yielded a list of key socioeconomic factors that influence adoption behaviour and those that can be used to identify key stakeholders to facilitate innovation transfer (Chapter 3 & 4). Impact evaluation studies in social-ecological contexts provided a list of variables that are often accounted for when evaluating resource conservation and management interventions (Chapter 5). I then illustrate how the variables selected were conceptualized in line with the conservation intervention and social-ecological setting studied here. Factors that were particularly relevant for the adoption of the conservation intervention were also included (Table 3).

Predictor variables in diffusion research

A critical focus of many diffusion studies is exploring why some people adopt and others do not. Studies that examine the influence of various determinants on adoption and diffusion processes have identified three key categories of adoptee traits that influence spread of innovations and speed of adoption: personality traits, socioeconomic status, and communication behaviour (Baerenklau & Knapp 2007, Greiner et al 2009). I therefore conducted a desktop review to identify factors that have been empirically shown to influence adoption behaviour and diffusion processes. A special consideration was given to studies that focus on uptake of environmental schemes.

Personality traits: Many adoption studies often correlate personality characteristics such as risk orientation, rationality or agency, psychological strength, self-confidence, and others with innovation adoption behaviour (Goldsmith 1984, Vanclay & Lawrence 1994, Young 2009). The emphasis on personality traits is underpinned by the notion that innovations would spread more rapidly among members who perceive them to be advantageous regardless of whether or not those innovations have objective advantages (Feder et al 1985, Rogers 2010).

Risk orientation: Risk orientation captures key perceptions of the individual about the present and future probability distribution of social and economic returns from investing in new ideas and practises (Mistian & Strand 2000). Indeed, of all personality traits associated with adoption, risk orientation is the most studied (Binswanger & Sillers 1983, Greiner et al 2009, Knowler & Bradshaw 2007). Earlier comparative studies on adoption and non-adoption yielded a general consensus that non-adopters of new technologies including innovative environmental schemes tend to be more risk averse than adopters (Feder et al 1985, Fernandez-Cornejo et al 1994). However, with the increasing number of new technologies and environmental schemes in different regions as well as empirical adoption studies in the recent past, this notion is challenged. Currently, there is lack of consistency in the relationship between risk orientation and adoption of new technologies and practices (including conservation interventions) in that both negative (Greiner et al 2009, Knowler & Bradshaw 2007) and positive (Barham et al 2004) relationships have been documented. Longitudinal studies that investigate risk attitudes and adoption of organic farming found the relationship to be non-existent between adopter categories over time (Läpple & Van Rensburg 2011).

Agency: In addition to risk orientation, a lot of attention has been paid on personal attributes that revolve around agency. People with higher agency particularly those that believe in using the most effective and realistic means to achieve personal development targets are often related with early adoption behaviour, e.g., uptake of novel farming technologies (Rogers 2010). Conversely, individuals with lower agency, often associated with being irrational and dogmatic tend to invoke fatalistic ways of reasoning that discourage investment in new farming technologies and environmental schemes (Fulton et al 2011, Rogers 2010). In the conservation context, agency - like many other personal attributes - has been shown to have dual effects (i.e., positive and negative) on conservation adoption decisions depending on the conservation intervention considered (O'connor et al 1999, Slimak & Dietz 2006).

Self-confidence and venturesomeness of individuals have also been shown, albeit to a lesser extent to influence individual‘s receptiveness to novel information as well as rate of adoption of innovations (Blau 1960). Early adopters of high cost integrated farming technologies and practices have been characterized by high self-esteem and being venturesome, whereas people that are less industrious with lower self-esteem remain skeptical about new technologies tend to be the slowest to adopt (Ram & Jung 1991, Rogers 2010). However, due to the difficulties associated with quantifying venturesomeness and self-confidence (Feldman & Armstrong 1975), recent empirical investigations rarely include these attributes. Depending on the specific attribute considered and the innovation to be diffused, personal attributes can either promote or constrain adoption (Gelcich et al 2005). Thus, although personality characteristics are a key part of the central tenets driving responses to adoption decisions, some personal attributes can unwittingly act as barriers and/or drivers for adoption (Greiner et al 2009).

Socioeconomic status: Taking a broad view on socioeconomic status, diffusion research demonstrate that differences in people‘s socioeconomic status account for more variance in likelihood of an individual's adoption behaviour than a vast majority of sociodemographic variables such as age, race, ethnicity, marital status, and gender (Morris & Venkatesh 2000). Attributes of socioeconomic status such as wealth, education, occupational diversity/multiplicity, size of firm, and ownership of key productive assets have often been used to classify adopter categories (Feder & Umali 1993, Guerin & Guerin 1994, Knowler & Bradshaw 2007, Mercer 2004). However, like personality traits, socioeconomic status can have both positive and/or negative effects on adoption and diffusion of innovations across societies, showing either positive or negative relationships depending on the complexity of the innovation and the social identity and experiences of the potential adopter (Ervin & Ervin 1982, Guerin & Guerin 1994, Knowler & Bradshaw 2007, Prokopy et al 2008). The lack of consistency in a vast majority of these characteristics in predicting adoption behaviour has led to unstructured adoption and diffusion processes around the globe (Makate et al 2018, Weiss et al 2018). I review them in turn.

Wealth: The effect of wealth on adoption decision including high-risk technologies is often shown to be positive (Arslan et al 2014, Boahene et al 1999, Rogers 2010). The underlying explanation to this relationship has been that people having higher material wealth tend to have greater capacity to deal with potential setbacks often associated with adoption of unproven innovations such as high-risk farming technologies (Cramb et al 1999, Knowler & Bradshaw 2007, Mercer 2004). In social-ecological settings however, when a higher level of wealth is associated with individuals that have a wide range of income generating activities, (i.e., occupational diversity) a negative relationship with adoption of conservation schemes is often observed. Alternative sources of livelihoods tend to reduce the need to conserve a shared resource (Gebremedhin & Swinton 2003). Indeed, these occurrences are prevalent in cases where income obtained from alternative income generating activities obscures the benefits accruing from investments in conservation of the common resource or when people's participation in other activities keep them away from the social-ecological system (Jansen et al 2006, Shively 1996).

Education: Education is shown to be a very important factor for early adoption of new technologies (Rogers 2010). A positive relationship between higher levels of education and technology adoption of environmental schemes has often been observed in developed societies. For example, a study by Burton et al (1999) showed that higher levels of education were positively related to early adoption of organic horticultural technology among flower farmers in Ireland, and the United Kingdom. Numerous investigations in developing countries have shown no association between levels of education and adoption of environmental schemes (D‘Souza & Mishra 2018, Feder et al 1985, Mwangi & Kariuki 2015). In fact, a few studies have shown that level of education can be negatively related to adoption, e.g., adoption of sloping agricultural land technologies in the Philippines (Sureshwaran et al 1996). In the conservation context, a vast majority of empirical studies have shown that level education is not likely to influence peoples conservation adoption decisions (Burton et al 2003, Hattam & Holloway 2007). Only a hand full of studies that focus on uptake of soil conservation interventions show education to be an important factor for early adoption (Diederen et al 2003, Läpple & Van Rensburg 2011, Rogers 2010). One possible explanation for the lack of directional relationship between education and adoption in developing countries is that the level of education for most people in rural settings is relatively low (i.e., between 0 to 4 years) compared to other diffusion studies conducted in developed societies where most people would have a higher range (~12 years) of education (Feder et al 1985, Lau et al 2018).

Occupational multiplicity: Occupational multiplicity, i.e., having multiple sources of livelihoods or income among members of a household, can serve as a buffer for potential setbacks and tend to encourage uptake of novel technologies (Knowler & Bradshaw 2007, Mercer 2004). Conversely, a number of empirical investigations on adoption of conservation farming practises and technologies have shown a negative relationship between occupational multiplicity and adoption decision (Cramb et al 1999, Gebremedhin & Swinton 2003). The underlying explanation to this negative relationship has been that income from other members of a household can be used to support many members of the household to hire labour force for efficient farming and productivity (i.e., intensification) – occurrences that often negate goals associated with widespread adoption of conservation schemes (Meyfroidt et al 2018). Other studies have also shown that occupational multiplicity and other variables denoting whether or not the farm household has fellow members engaged in income generating activities may not influence adoption altogether (Burton et al 2003, Genius et al 2006). The lack of a directional relationship is supported by the assertion that having multiple sources of income from independent members of a household may not always translate into greater financial capacity on all members of the household (Gebremedhin & Swinton 2003).

Ownership of productive assets: Ownership status of key productive assets is recognized as a major determinant of adoption of new farming technologies and practises (Ramasamy et al 1992, Tiongco & Hossain 2016, Upadhyaya et al 1993). Prior research has however shown that the nature of ownership, i.e., lease versus owned can determine the speed with which adoption of agricultural conservation practises and technologies among farmers occur (Tiongco & Hossain 2016, Upadhyaya et al 1993). Where, ownership of key productive assets such as land and other capital assets is associated with access to subsidies – an influential aspect on conservation adoption decision, ownership status has been shown as key factor to rapid adoption of innovative farming practises such as organic farming (Feder & Umali 1993, Läpple 2010).

Size of firm: Though this variable is presented in a variety of ways, e.g., size of farm space or existing capital assets overall trends show a positive relationship to adoption (Amsalu & De Graaff 2007, Feder 1980). Specific longitudinal studies have revealed that farms that are bigger tend to adopt conservation interventions earlier (Diederen et al 2003), highlighting that size of firm could be important during the early stages of adoption processes. Only a few studies show that an increasing farm size can be negatively related to adoption of novel farming practises such as organic farming (Burton et al 2003, Dadi et al 2004). This suggest that in certain contexts farmers who operate larger farms can be less receptive to novel farming technologies especially if it is too costly to apply the innovation at a large scale (Hayami & Ruttan 1985). A few longitudinal diffusion studies on adoption of organic farming in developed societies have found no differences in the positive relationship between farm size and early, medium, or late adoption (Läpple & Van Rensburg 2011). This implies that farm size can be a robust indicator of adoption over time.

Formal leadership: Numerous empirical studies show a positive relationship between formal leadership and conservation adoption decisions (Feder & Umali 1993, Knowler & Bradshaw 2007, Rogers 2010). Longitudinal diffusion studies have indeed shown that formal leaders are often early adopters of new ideas (Harper et al 2018). This is because formal leadership is often associated with opinion leadership, strong social ties, and command a lot of respect from other members of the society especially in rural social systems (Flynn et al 1996, Loewe & Dominiquini 2006, Valente & Pumpuang 2007). Key underlying explanation for this trend is that having a leadership role tend to increase one's chances of accessing crucial conservation information due to the frequent contact between local leaders and extension or external change agents (Bodin & Crona 2008).

Innovation knowledge: A vast majority of empirical studies point to a big positive connection between innovation knowledge and adoption particularly during the early stages of the adoption process (Feder & Umali 1993, Fuglie & Kascak 2001, Knowler & Bradshaw 2007, Mercer 2004, Rogers 2010). For example, studies on adoption of organic farming in Ireland showed a consistent positive effect of innovation knowledge on early adoption among farmers (Läpple & Van Rensburg 2011). However, an important caveat (i.e., credibility of information source) is often put on this positive relationship. For example, despite the elegance, efficiency, productivity, and/or ecologically sustainability of soil and water conservation techniques in Burkina Faso, very few people adopted because of credibility issues of the information source (Sidibé 2005). Agricultural experts with limited knowledge of organic farming and therefore perceived to have less credibility have also in the past led to discouragement among farmers to convert to organic farming in Ireland (Wheeler 2008).

Provision of incentives: Consensus stipulates that incentives can positively influence adoption behaviour. For conservation interventions that require huge investment capital or other costs associated with adoption, inadequate incentives has been highlighted as a major constraint to the rapid adoption of conservation interventions (Feder & Umali 1993, Knowler & Bradshaw 2007). However, in societies where people are heavily dependent on aid, e.g., communities in but not limited to developing countries, offering incentives can undermine innovation diffusion processes. To support their argument, they contend that provision of incentives can create false hope – a scenario that often discourage investment in innovative technologies over the long term (Eliasen et al 2013, Feder et al 1985, Läpple & Van Rensburg 2011).

Age: Aside from personality and socioeconomic status attributes, another key sociodemographic attribute that is often included in adoption studies is age. In any social system age may serve as a surrogate for other socioeconomic conditions, e.g., work experiences a person has accumulated over time (Knowler & Bradshaw 2007). As such, many studies have analysed the relationship between age and adoption behaviour in different contexts around the globe. Overall, a vast majority of adoption studies show inconsistent (i.e., both positive and negative) relationships between age and adoption behaviour (Feder & Umali 1993, Jung & Kim 2017, Knowler & Bradshaw 2007). For example, studies that analysed the effect of age on the uptake agricultural conservation interventions show that older farmers tend to be more resistant to take up new environmental practises with long-term conservation objectives (Sayer & Campbell 2004, Tiwari et al 2008). The limited motivation to adopt is underscored by the notion that older farmers often feel that the expected ecosystem change may not occur in their lifetimes (Feder & Umali 1993). In contrast, younger people often associated with longer planning horizons have been shown to be more receptive to new conservation ideas and tend to invest more in conservation (Bultena & Hoiberg 1983, Crona & Bodin 2006, Feder & Umali 1993, Knowler & Bradshaw 2007). Specific longitudinal diffusion studies have indeed shown that that early adopters are the youngest to adopt organic farming practises and technologies (Barham et al 2004, Läpple & Van Rensburg 2011). However, a sizable amount of empirical investigations also reports a positive relationship between age and adoption of conservation interventions. For example, it has been shown older farmers that exhibit a higher level of environmental concern (Burton et al 2003, Läpple 2010), tend to embrace farming practices that prioritize protection over destructive behaviour to safeguard their traditional resource (Jagers et al 2012). In cases where old age is associated with opinion leadership, a positive relationship with uptake of novel fisheries management schemes has been reported (Bodin & Crona 2008). Equally, other studies have shown that the relationship between age and adoption decision can be non-existent (Amsalu & De Graaff 2007, Rogers 2010, Shiferaw & Holden 1998).

Communication behaviour: One of the primary research findings of diffusion research was that adoption over time follows the two-step-flow hypothesis where opinion leaders[9] are made aware of innovations through external exposure, which increases their propensity to adopt early; and in a second step they influence opinion followers (Rogers & Cartano 1962, Valente & Pumpuang 2007, Weimann 1982). In other words, the longstanding theory of diffusion has argued that early adopters tend to have more sources of external influence in terms of cosmopoliteness[10] and exposure to mass media than late adopters (Merton & Merton 1968). In accordance with these contributions, it is often argued that whereas external

[9] Opinion leadership in this context is measured by the number of network nominations received in a social network indicating the flow of interpersonal influence (Rogers & Cartano 1962, Valente & Pumpuang 2007).

[10] A cosmopolite is an individual who is oriented to the world outside of his or her local system and who relates his or her local system to the larger environment by providing links to outside information (Merton 1968, Valente 1996a)

influences are generally responsible for making individuals aware of innovations, it is often interpersonal influence with friends and neighbours that leads to actual adoption (Valente 1996c). Put explicitly, a large network comprised of a few direct ties and multiple indirect ties is often associated with opinion leadership and early adoption behaviour, whereas interpersonal communication ties that are more instrumental for persuasion are linked to late adoption (Valente 1996c). Against this background, there is therefore a general consensus that communication behaviour is key for late adopters (Rogers 2003).

Social network science however provides a set of new concepts and analytical strategies, e.g., SNA for understanding how human behaviour, e.g., adoption of innovations, is socially constructed as an outcome of an actor‘s relationship with others (Centola 2015). Researchers have explored a number of topological properties of social networks such as centrality metrics, measures of brokerage, contagion effects, and network clustering to understand how network processes relate to the spread of innovations (Centola 2018, Louch 2000, Valente et al 2008). I review them in turn.

Level of social connectivity: Actors that display high degree centrality (i.e., have many direct ties) tend to be more popular in a network (Wasserman & Faust 1994). By maintaining many more times the number of ties than the average person does popular actors or high degree nodes are more likely to access novel information by connecting to others who are in positions that are different from them (Gladwell 2006). Depending on the information extracted from their social world, these connections can translate into a wide variety of favourable outcomes, spanning social obligations such as adoption of new ideas, practise, and technologies (Valente 1996c). Indeed, diffusion literature argues that early adopters tend to be more integrated in the social community and may have strong social ties with other innovators in the social system (Gladwell 2006).

Contagion effect: This is a type of social influence on people's behaviour through social ties and association (VanderWeele 2011). Current studies on contagion processes builds on prior research on peer effects and interpersonal influence (Burt 1987, Christakis & Fowler 2013). Empirical analyses on contagion effects with social network data have shown that contagion processes can play an important role in diffusion process of certain behaviours such as the spread of smoking habits among other social states, e.g., loneliness (Cacioppo et al 2009, Christakis & Fowler 2008). Interestingly, the nature of social influence or contagion effects can occur in different forms. For example, obesity among people has been shown to spread through two socially connected actors (i.e., one individual influencing another by changing weight-related behaviour e.g., diet) (VanderWeele 2011). Conversely, other empirical studies have shown that person-to-person influence may be insufficient to facilitate innovation transfer especially if the knowledge, practise or technology is complex (Reagans & McEvily 2003). To advance this suggestion, several scholars have argued that social cohesion, defined as third-party ties around relationships can facilitate complex contagion processes among social systems because it congregates homogenous actors thereby decreasing the impediments associated with node-to-node social influence (Reagans & McEvily 2003).

Network clustering: Clustering is considered one of the most important properties in classical networks (Levine & Kurzban 2006). Clustering, often associated with social consolidation of shared norms and practices (Centola & Baronchelli 2015), has been shown to promote diffusion of novel information and practises among people with shared social identities (Centola 2010). Network clustering has also been shown to increase coordination (McCubbins et al 2009), cooperation, and trust among individuals in social systems (Burt 2004). In some cases, these closed network clusters have provided a special ingredient that often can have a direct positive effect on contagion and diffusion process that seek behaviour change (Centola & Macy 2007, Opsahl 2013), and the transfer of complex knowledge (Centola 2018, Hansen 1999).

However, it is equally argued that close-knit clusters tend to congregate homogenous groups – a situation that often undermines knowledge diversity, innovativeness, and transfer of knowledge among individuals between groups (Levine & Kurzban 2006). In other words, while new information or knowledge can diffuse well within clusters, it travels less well between them, especially when it is complex (Hansen 1999). By creating and reinforcing isolation as well as cutting externalities, network clustering may eventually pose a special challenge to diffusion processes (Levine & Kurzban 2006). Indeed, close-knit groups that tend to be cohesive with few opportunities to create more crosscutting ties that can improve access to novel information and spread of innovations across systems (Centola 2010, Centola 2015). Put simply, network clustering can impede complex contagion processes between clusters (Granovetter 1983). Therefore, like personality traits and socioeconomic status, patterns of communication behaviour, and network positions can all have both potentiating and/or inhibiting effects on adoption and diffusion of innovations, showing either positive or negative relationships depending on the context.

Type of networks

In the network context, diffusion is a communication process in which adopters persuade non-adopters to adopt innovations (Rogers 1995, Valente 1996c). Network analysis therefore serves as a vital tool to better understand the flow of influence enabling researchers to determine who influences whom in the network (Valente 1996c). Although diffusion of innovations research has been greatly enhanced by network analysis, the role of network structure and how the structure relate to conclusions and inferences drawn from diffusion processes is still an open debate (Robins 2015). Understanding the different types of network structure will permit more exact specifications of who influences whom during the diffusion process (Robins 2015, Valente 1996).

Network science identifies three types of network structure, i.e., random, scale free, and small-world networks (Robins 2015). These network structures are often classified according to two independent structural features, i.e., clustering coefficient and average node-to-node distance (average shortest path length) (Barabasi et al 1999, Bollobas et al 2001, Choromanski et al 2013). The two independent features can have different effects on diffusion processes depending on the complexity or simplicity of the innovation to be diffused.

Random networks can take the form of regular lattices or the Erdos-Renyi graphs (Barabasi et al 1999, Robins 2015). Regular lattices are artificial networks that have the lowest heterogeneity (e.g., the number of connections each node has is more or less the same) and lowest randomness (the probability of any two randomly chosen nodes to be wired to each other is very low or zero) (Barabasi et al 1999). The more extreme random graphs, often referred to as Erdos-Renyi graphs, are generated by starting with a disconnected set of nodes that are then paired with a uniform probability, i.e., network ties occur independently and with probability p – easily estimated as the density (Robins 2015). Because random networks are based on independent ties, they do not offer a good representation of empirical social networks and therefore network patterns such as reciprocity or closures - that are often critical in any diffusion process - are least expected (Lusher et al 2013). For this reason, random graphs are only useful as null models against which to compare more complex effects in diffusion processes.

Most real-world social networks however do not have homogeneous distribution of degree that regular or random networks have. The number of connections each node has in most networks varies greatly and they are positioned somewhere between regular and random networks. In other words, where the connections between the nodes in a regular graph are rewired with a certain probability, the resulting graphs are between the regular and random in their structure and are referred to as small-world networks (Watts & Strogatz 1998). Small-world networks are very close structurally to many social networks in that they have a higher clustering coefficient and almost the same average path length than the random networks with the same number of nodes and edges (Choromanski et al 2013). Small-world networks usually have high modularity (groups of the nodes that are more densely connected together than to the rest of the network) (Watts & Strogatz 1998). Many empirical network graphs tend to exhibit features of small-world networks, e.g., social networks. Because small-world networks tend to contain cliques (i.e., sub-networks between almost any two nodes within them) among other network configurations, their properties permit the use of numerous network effects in diffusion studies that utilise the network approach (Robins 2015).

A scale-free network is a network whose degree distribution follows a power law, at least asymptotically (Clauset et al 2007, Cohen & Shlomo 2003). The most notable characteristic in a scale-free network is the relative commonness of vertices with a degree that greatly exceeds the average (Choromanski et al 2013). The clustering coefficient distribution in a scale-free network decreases as the node degree increases – which means that removing randomly any fraction of nodes from the network will not destroy the network (Cohen & Shlomo 2003). This in turn suggests that diffusion processes in scale-free networks are immune from fragmentation even when one or more stakeholders are removed from the network. Many empirical networks have been reported to be scale-free although statistical evidence still remains inconclusive due to the developing awareness of more rigorous data analysis techniques. As such, the scale-free nature of many networks is still being debated by the scientific community.

Conceptualization of predictor and control variables

Here I illustrate how the variables selected were conceptualized in line with the conservation intervention and social-ecological setting studied. Where a variable is used in multiple chapters either as a predictor or control (i.e., predictor for adoption - chapter 3; predictor for selecting key players in conservation diffusion - chapter 4; or control factor for evaluating conservation outcomes on people - chapter 5), I provide the corresponding theoretical justification. Factors that were particularly relevant for the adoption of the conservation intervention (i.e., the escape slot trap) are included in this section (Table 3). I also include other factors that had specific relevance for controlling wellbeing conditions based on the conservation intervention and the social-ecological setting studied here (i.e., fishing communities). It is important to note that control variables were only used in chapter 5.

Personal attributes

In terms of personality traits, I included agency and risk orientation. Particular attention was paid to the impact of personal attributes on adoption decisions. While more recent literature agrees on the importance of the attitudes or subjective norms on people's adoption decision, this is often incorporated into empirical analysis with the inclusion of only one question in the survey (Burton et al 2003, Genius et al 2006). In this analysis multiple set of attitudinal statements are used in order to assess fishers' attitudes towards personal attributes. This approach is consistent with foundation studies that underline the importance of measuring attitudes with multiple statements (Fishbein & Ajzen 1975).

Agency: Agency conveys the notion about what people can do with that they have, e.g., how people engage with others or the environment to achieve certain goals and meet their needs (Woodhouse et al 2015). In diffusion research, it is often argued that higher agency tends to relax the constraints needed for adoption of innovations (Rogers 2010). Agency was used as a predictor for adoption (chapter 3; Table 3).

To assess agency, I used three attitudinal questions. First, respondents were asked to state the extent at which their personal capabilities determine success in fishing. Second, I asked respondents to indicate whether they believe success in fishing is mostly determined by their relationship with God/Allah. Third, respondents were asked to state whether they believe their success in fishing is mostly determined by traditional practices, such as offering sacrifices or and praying at traditional shrines. The three questions were deemed important because peoples metaphysical believes have been shown to be crucial in determining hopes and aspirations for the future among fishers in coastal Kenya (Abunge et al 2013). Moreover, it has been shown that rational fishers that believe in using the most effective and realistic means to increase their catch tend to exhibit higher agency and propensity to embrace change in management of fisheries (Jentoft & Chuenpagdee 2009). In all questions, fishers were presented with multiple choices, (i.e., No, A little bit, Yes, or Don‘t know). For question 1, a YES response was associated with agency (i.e., ability of an individual to use the most effective means to increase catch), whereas all other responses (including don‘t know) were interpreted as a lack of agency. The order was however reversed for question 2 and 3 in that a YES response was associated with a lack of agency, whereas other responses were linked to agency. Using the set of binary variables created as explained above, I ran a PCA (principal component analysis) to create an agency score from the first axis (88.3% of total variance explained).

Risk orientation: Risk is defined as ‗the chance of something happening that will have a negative impact on our objectives‘ (Coleman 2011). The impacts of attitudinal characteristics such as perceptions about risk are of critical importance when people reflect whether or not to take up novel conservation interventions (Barham et al 2004). In the fisheries context, specific studies have shown that fishers tend to be risk seekers compared to other members of the general population (Cinner et al 2010). However, the influence of fishers‘ perception of how they behave under uncertainty (risk orientation) on their conservation adoption decisions is not well documented. Risk orientation was used in chapter 3 as a predictor for adoption (Table 3).

Risk orientation was examined as a latent trait comprised of three questions. First, fishers were asked to indicate the number of times per year they go exploring for new fishing grounds. I used the mean number of days that fisher's explore new fishing grounds per village to distinguish between risk seekers and risk averse. Fishers that reported more days than the village mean were considered risk seekers whereas those who reported numbers below the village mean as risk averse. Second, respondents were asked to state their opinion when they thought about taking a risk, (i.e., the words that came to their mind first). Those who perceived risk taking as an opportunity were classified as risk seekers while those who perceived taking risk as loss risk averse. Indeed, several studies have shown that people who perceive challenges (i.e., risks) as opportunities tend to embrace and invest more in conservation (O'connor et al 1999, Slimak & Dietz 2006). Third, fishers were asked to indicate how they would behave under uncertainty of catch, e.g., whether they would be willing to try something new, (i.e., a new fishing technique or fishing site, even if it meant that while learning they might catch less, but after learning catch more). Fishers were required to indicate either No, A little bit, Yes, or Don't know. Those who answered YES were classified as risk seekers otherwise risk averse. Finally, respondents were asked to indicate what their best friends would say about them taking risks. Fishers were presented with four categories of choices, i.e., [1] You're a real gambler [2] You're willing to take risks after doing adequate research [3] You're cautious about risks [4] You avoid risks at all costs. Real gamblers were considered risk seekers, all others were considered risk averse. Coded responses about risk orientation were included in a PCA and component scores created from the first axis (83.1% of total variance explained).

Socioeconomic status

Education: Education is considered a key ingredient in shaping peoples opinion towards change (Lau et al 2018, Lin 1991). In the conservation literature, it is widely hypothesized that highly educated people are likely to comprehend novel conservation ideas more quickly and accurately than less educated people do (Pomeroy & Berkes 1997). Education is defined here as the maximum grade the fisher completed in formal education. In rural fisheries settings, level of education can be an indicator of social status in a community (Cinner et al 2009a). Persons with higher social status in rural social-ecological settings can have easier access to collective benefits, e.g., resource management information at the expense of others (Ribot 2002), a scenario that can positively influence conservation adoption decisions. Highly educated persons can derive prestige, command respect, and influence in rural social-ecological settings from their frequent engagement with external environmental experts or actors – circumstances that often influence people‘s relational and subjective aspects of wellbeing (Bodin & Crona 2008, Coulthard et al 2011, Olsson et al 2004). Against this background, education was used in all three chapters (i.e., chapter 3 – as a predictor for adoption; chapter 4 – a predictor for selecting key players in conservation diffusion; and chapter 5 – as a control variable for evaluating conservation outcomes on people) (Table 3).

Occupational multiplicity: Having alternatives to livelihoods can serve as a buffer for potential setbacks and tend to encourage uptake of novel environmental and conservation schemes (Knowler & Bradshaw 2007). Occupational multiplicity was measured as total number of income generating activities within a fisher household. The influence of occupational multiplicity on a wide range of fisheries management topics such as perceptions about resource conservation and management preferences is well studied (Cinner et al 2009a, Daw et al 2012, McClanahan et al 2012). Fishers whose fellow householders have multiple income generating sources can be an indicator of wealth (Cramb et al 1999). Material assets among fishers has been associated with their level of occupational multiplicity (Cinner 2014). Higher occupational multiplicity can provide an opportunity for other members of the fisher household to supplement their incomes - a key aspect that can encourage investment in conservation (Cinner et al 2009a, Cramb et al 1999). However, in other natural resource management contexts, having alternatives to livelihoods may serve to reduce the need to conserve a common resource (Mercer 2004). Against this background, occupational multiplicity was used in two chapters (i.e., a predictor for adoption - chapter 3; and a control variable for evaluating conservation outcomes on people - chapter 5) (Table 3).

Ownership of productive assets (fishing gear and vessel): In the agricultural economics, ownership of key productive assets such as land and other capital assets can be major constraints to the rapid adoption of novel farming technologies and environmental schemes (Feder & Umali 1993, Läpple 2010). Indeed, conservation practitioners tend to prefer persons with full ownership of key productive assets when offering incentives – a key factor that can influence conservation adoption decision. In the fisheries context, possession of productive fishing assets such as full ownership of a fishing gear and vessel is critical in determining success in fishing (McClanahan et al 2015). Gear ownership is even more important because fishing cannot happen without a fishing gear. Gear ownership was simply determined by whether or not one owns a fishing gear (in this case a fishing trap) and was used in chapter 3 as a predictor for adoption of the escape slot trap. Because of the high cost associated with fishing boats, ownership of a fishing vessel can be an indicator of wealth and is often associated with social status in fishing communities (Pollnac & Crawford 2000). Accordingly, I used vessel ownership (denoted as productive assets in chapter 4) to identify key players in conservation diffusion (Table 3).

Material style of life (MSL): In many cases, the effect of wealth on adoption decision including high-risk innovations is often shown to be positive (Arslan et al 2014, Boahene et al 1999, Rogers 2010). The underlying explanation to this relationship has been that people having higher material wealth tend to have greater capacity to deal with potential setbacks often associated with innovations such as high-risk conservation interventions (Cramb et al 1999, Knowler & Bradshaw 2007, Mercer 2004). In rural social-ecological settings, wealthy people or more privileged individuals (elites) tend to be opinion leaders that dominate decision-making processes at the expense of other groups – attributes that are often associated with early adoption behaviour (Leonard-Barton 1985, Valente & Davis 1999, Valente & Pumpuang 2007). By having more access to collective benefits (elite capture) such as access to information related to resource management (Ribot 2007), wealthy people can strategically align, adjust, and adopt resource exploitation strategies in line with existing laws and regulations ahead of others (Ostrom 2007a). In sum, wealth (MSL) can be an indicator of social status in a community in developing countries where wealthy people can derive a lot of respect, prestige, and influence in various social systems (Cinner et al 2009a). Indeed, people‘s level of wealth can influence their objective and subjective aspects of wellbeing such as material assets and social relationships (Bodin & Crona 2008, Coulthard et al 2011, Olsson et al 2004). Against this background, MSL was used as a predictor in all three chapters. In chapter 5, I used material style of life as an indicator of material wellbeing (Table 3).

In computing material wealth, I used material style of life (MSL, i.e., an indicator of wealth based on a wide range of household possessions and structure (Cinner et al 2009a). I examined a list of 55 items including lighting, transport, household electronics, cooking materials, household structures (such as wall, roof, and floor), among others. I treated all household items as stand-alone attributes for indicators of wealth. These include generator, electricity, solar panel, car battery, TV, DVD, radio cassette, electric fan, mobile phone, smart phone, satellite dish, refrigerator, air conditioning, and piped water. A similar approach was followed for means of transport, land, and investments assets. Regarding transport, I asked respondents to show whether they possess the following: bicycle, motorcycle, vehicle, or other. Respondents would also indicate whether they own land, livestock, cows, poultry, plot, business kiosk, dugout canoe, outrigger, dhow (a different type of vessel), outboard, inboard, or fish freezer as investments assets. For land, respondents were prompted to indicate the exact number of acres owned while actual numbers were to be given for livestock, cows, poultry, and plot/s owned. Conversely, dummy variables (1=rich and 0=poor) were created for other indicators of wealth, i.e., lighting, cooking items, roof material, floor material, and wall material. For lighting, any respondents using light bulb powered by electricity was considered rich while those using hurricane lamps, candles, solar light, and kerosene wick were classified as poor. Regarding transport, respondents with vehicles or motorcycles were categorised as rich while those with only bicycles or otherwise were considered poor. Respondents using gas or electric cookers were considered rich while those using charcoal, kerosene, or firewood as cooking material were classified as poor. Respondents whose houses were roofed with iron sheets or tiles were regarded as rich while those whose houses had thatched roof or otherwise were categorised as poor. For floor material, respondents with finished tiles and cement were classified as rich while those with dirt/soil, bamboo/palm, plank wood were regarded as poor. Finally, respondents whose houses were constructed using stone block and cement were considered rich while those with bamboo/thatch, metal, mud wood/plank or otherwise as wall material were classified as poor. This categorisation is based on existing research that uses the material style of life index (Cinner et al 2009a) and personal experiences of the authors who had a thorough knowledge of the communities' lifestyle. A material style of life (MSL) metric was created from the first axis of a PCA (36.6% of total variance explained).

Size of firm (number of traps): The influence of size of firm is central in most conservation adoption studies (Amsalu & De Graaff 2007, Feder 1980). Depending on the intervention, this variable is however presented in a variety of ways. For, example, studies that focus on adoption of farming practises such as organic farming and soil conservation tillage have used acreage (size of farm space) as a proxy of size of firm (Bultena & Hoiberg 1983, Clearfield & Osgood 1986, Tiwari et al 2008). Studies that analyse adoption patterns of agricultural conservation technologies have used existing capital assets to denote size of firm (Adesina & Zinnah 1993, Feder 1980, Fuglie & Kascak 2001). Other studies looking into adoption intensity on conservation technologies have framed the influence of size of firm as the number of objects or units that can potentially be replaced or changed by the adopter (Mwangi & Kariuki 2015, Strauss et al 1991, Ugochukwu & Phillips 2018). Regardless of how the variable is created and presented, overall trends show a positive relationship to adoption. Here a proxy denoting the number of traps owned by a fisher describes the influence of size of firm and was used in chapter 3 as a predictor for adoption (Table 3). Using the number of objects or items that can be replaced or changed in analysing adoption behaviour is consistent with previous studies that show people are likely to depict differential adoption intensities, i.e., try some and maintain others when adopting innovations with trialability[11] characteristics such as the one studied here (Arslan et al 2014, Rogers 2010).

Formal leadership: Leadership is often highlighted as an important component for adoption of conservation interventions (Black et al 2011, Harper et al 2018). Having a leadership position is often associated with opinion leadership and strong social ties - key determinant of adoption behaviour (Harper et al 2018). I define formal leaders as individuals who are elected as leaders of the Beach Management Unit (BMU) responsible for community-based coastal

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[11] In diffusion research, trialability refers to the degree to which an innovation may be experimented on a limited basis (Rogers 1995).

and marine management in my study sites. In Kenya, conservation practitioners tend to work closely with community leaders, e.g., BMU leaders when initiating environmental conservation and management initiatives at the local level (Olsson et al 2004, Ostrom 2007b, Pretty 2003). Because of their social status and position in the co-management process, BMU leaders are expected to adopt, sustain, and maintain environmental and management actions over time in order to increase visibility and awareness on conservation efforts at the local level (Bodin & Crona 2008, Olsson et al 2004). Due to their positions and responsibilities formal leaders carry in the wider community, formal leadership can therefore have an impact on their social relationships with others in the social system – a key determinant of relational wellbeing (Bodin & Crona 2008, Coulthard et al 2011, Olsson et al 2004). It is against this background that formal leadership was used in all three chapters (i.e., chapter 3 - as a predictor for adoption; chapter 4 – to select key players in conservation diffusion; and chapter 5 – a control variable for evaluating conservation outcomes on people) (Table 3).

Innovation knowledge: Knowing about the existence of an innovation a critical step in the adoption decision process (Lynne et al 1995). Put plainly, no adoption can occur without initial knowledge of the innovation. Thus, innovation knowledge has been acknowledged to play a critical role in many diffusion processes (Genius et al 2006, Khataza et al 2018). A well-known concept in the diffusion literature is that innovation knowledge tends to reduce perceived risks and uncertainties associated with adoption (Feder & Slade 1984, Marra et al 2003). Therefore, having principle knowledge of any innovation is likely to significantly influence people‘s adoption decisions (Dewar & Dutton 1986, Ostlund 1974, Rogers 2010). To capture innovation knowledge, respondents were asked to elaborate the extent of their prior knowledge of the innovation, i.e., awareness knowledge, how to knowledge and principle knowledge of the innovation (Rogers 2010). The three questions were framed as follows: awareness knowledge, i.e., whether or not one had heard about the innovation before; how to knowledge, i.e., whether one fully understands the purpose of the innovation; and principle knowledge, i.e., whether one has the ability to fabricate the innovation[12]. I included the credibility of information source in addition to the three questions highlighted above. This is important because credibility of the information source of any novel idea can determine whether or not people will embrace that idea (Shepherd & DeTienne 2005, Wiig 2000). Here, respondents were asked to rate the level of credibility of the source of innovation knowledge. A source regarded as completely credible had a higher score of four while a score of one describes an injection point that is not credible. The PCA approach was used to compute average scale scores of innovation knowledge (84.2% of total variance explained). Innovation knowledge was used as a predictor for adoption (chapter 3; Table 3).

Provision of incentives: In order to increase the uptake of conservation interventions, provision of incentives is considered an important and influential ingredient (Eliasen et al 2013). This form of coercive pressure can influence adoption for a number of reasons. Firstly, offering incentives can be a strategy for getting to the critical mass of early adopters who are often needed to accelerate diffusion processes (Valente & Davis 1999). Secondly, provision of incentives can shape adoption inevitability perceptions (i.e., by implying that the innovation is very desirable and adoption is inevitable) (Rogers 2010). In this study, I had instances where some fishers were given the innovation to carry out experimental fishing on a trial basis. As indicated in innovation diffusion theory, this can be considered as offering incentives because the new gear was provided at no cost. Provision of incentives was used in chapter 3 as a predictor for adoption (Table 3).

[12] In diffusion research, innovation knowledge is three fold (awareness knowledge, how-to-knowledge, and principle knowledge). Awareness knowledge simply refers to whether one has information that an innovation exists. How-to-knowledge consists of information necessary to use an innovation properly whereas principle knowledge captures the functioning principles underlying how the innovation works (Rogers 1995).

Age (sociodemographic variable): Age, expressed as age of the fisher in years is a key sociodemographic variable that was included because of its relationship with other socioeconomic attributes such as work experience (Tiwari et al 2008). In fisheries settings, if old age is correlated with long years of fishing experience could carry important practical implications for fisheries management (McClanahan et al 2012). For example, in co-managed fisheries managers tend to engage fishers with significant longevity in co-management process due to their extensive knowledge base, traditional knowledge, and intellectual outlay about fishing (Bodin & Crona 2008). Through these collaborative arrangements, older fishers tend to have easier access to fisheries management information than their young counter parts – a scenario that can have a positive influence of on conservation adoption decision (Mbaru & Barnes 2017). Indeed, work experiences a fisher has accumulated over time can shape perceptions towards various components about fishing or the broader fishing community (McClanahan et al 2012). From a societal view point, age can also determine how people respond to various aspects about their quality of life (Cinner et al 2009a). To predict adoption, I used age of the fisher in (chapter 3; Table 3). However, given the relationship between age and work experience, I used the number of years spent actively in fishing (i.e., fishing experience) as a predictor for selecting key players in conservation diffusion (chapter 4; Table 3). In fisheries settings, fishing experience can determine whether or not one‘s opinion is respected by peers in a fishing community (McClanahan et al 2012). Other socioeconomic and sociodemographic factors that were included as control variables are access to credit, fishing dependency, and marital status. Access to credit can be a reflection of how individuals relate with others especially where people derive financial support from other members of the community (Cinner 2014). Where fishing is main source of livelihood, dependency on fishing can shape a myriad of perceptions about fishing activities which obviously can have an effect on subjective livelihood wellbeing (Gurney et al 2014). Marital status can be a potential barrier that can inhibit some members of a society from accessing certain collective benefits (Bene & Merten 2008). In rural fishing communities, marital status can also be a key determinant of social differentiation among people potentially affecting social relations (Geheb et al 2008). As such, marital status is often accounted for when evaluating management interventions in fisheries social-ecological settings (Cinner et al 2010, Coulthard et al 2014, Gurney et al 2015) (Table 3).

Social network processes

Naturally, when innovations are initiated, a small proportion of individuals are expected to adopt. Once the critical mass is firmly established, innovations are expected to propagate through the social system. During this time, communication behaviour (more so social networks) is thought to play a major role in determining the spread of innovations and speed of adoption (Golub & Jackson 2010, López-Pintado 2008). A review of empirical studies show that interpersonal communication behaviour tend to minimise risks and uncertainties associated with innovations thereby facilitating spread of innovations (Feder & Umali 1993, Goldsmith 1984, Greiner et al 2009, Lapinski et al 2018).

Table 2. Number of respondents interviewed in each village during the three sampling periods, i.e., baseline surveys (T_0), first follow-up surveys (T_1), and second follow-up surveys (T_2). Total number of actors in the social network in each village is shown in parenthesis. Categories of adopters over the three sampling periods in experimental villages (i.e., where the escape slot trap was introduced) are shown in the last two rows.

	Number of respondents (# actors)						
Sampling period	Village_a	Village_b	Village_c	Village_d	Village_e	Village_f	All sites
Baseline (T_0)	34(85)	43(127)	43(102)	33(78)	45(116)	40(112)	238
1st follow-up (T_1)	33(84)	59(152)	49(113)	36(85)	40(73)	42(82)	259
2nd follow-up (T_2)	31(88)	57(146)	45(111)	31(111)	41(76)	41(116)	246
	Adopters (dis-adopters) in experimental villages						
1st follow-up (T_1)		11	10	7		11	39
2nd follow-up (T_2)		24(5)	10(2)	11(3)		20(6)	65(16)

Table 3. Description of predictor variables used in chapter 3 and 4 and control variables used in the chapter 5. Material style of life was used as a predictor variable in chapter 3, 4, and 5.

Variable type	Variable name	Description	Ch.3	Ch.4	Ch.5	Data type
Personal attributes	Agency	Multiple questions on perception about success in fishing	√			PCA score
	Risk orientation	Multiple questions about risk orientation	√			PCA score
Socioeconomic status	Formal leadership	Whether respondent holds a leadership position in the community	√	√	√	Dummy
	Material style of life	Indicator of wealth based on household possessions and structure	√	√	√	PCA score
	Occupational multiplicity	Number of income-generating activities associated with the respondent"s household	√	√	√	Continuous
	Education	Highest grade completed	√	√	√	Continuous
	Fishing experience	Number of active years spent fishing		√		Continuous
	Productive assets	Whether respondent owns a fishing vessel		√		Dummy
	# Traps	Number of fishing traps used by a fisher	√			Continuous
Sociodemographic & other variables	Innovation knowledge	Multiple questions about prior knowledge of the escape slot trap	√			PCA score
	Age	Age (in years)	√		√	Continuous
	Gear ownership	Ownership of the fishing gear used	√			Dummy
	Provision of incentives	Whether a fisher was given escape slot trap at inception	√			Dummy
	Fishing dependency	Whether fishing is primary source of livelihood			√	Dummy
	Marital status	Whether respondent is married			√	Dummy
	Credit access	Whether respondent has access to financial support			√	Dummy

PCA = principal component analysis.

Different network properties in people‘s social networks can have important influence on behaviour change (Centola 2015). In my analysis having adoption as the outcome variable, I include five key network effects that have been widely used to model behaviour in social networks (Table 3). These include network popularity, activity, clustering, and contagion effects (Lusher et al 2013).

Popularity: Network popularity refers to general levels of social connectivity (Lusher et al 2013). Popular actors tend to have a higher number of direct ties has been positively related to trust and influence in social networks. Because of their ability to connect to a huge number of people quickly poplar actors are associated with the spread of complex innovations that seek behavior change (Freeman 1978, Tsai & Ghoshal 1998).

Activity: Unlike popular actors that often maintain numerous connections with many friends and acquaintances, actors that are more active in a network tend to maintain ties with other actors for the benefit of receiving or giving specific information based on the type of social network (i.e., type of network tie or question involved) (Lusher et al 2013). Actors that are more active in a given network tend to be information gatherers or disseminators of the specific network question/s under consideration (Gladwell 2006). They critically analyse and evaluate the information they derive from the network before passing their evaluations to others. In many cases, their evaluations may make or break the tipping of diffusion process (Gladwell 2006). Active actors can also determine or regulate the type of information that flows through the network.

Though network studies does not argue this explicitly, their description of active actors suggests that actors who were generally more active in a given network can be specialized in areas of expertise covered in the network questions (Lusher et al 2013). For example, in fisheries social-ecological settings where fishing is characterized by a multiplicity of gears, species, and vessels with various capacities there can be many active actors in particular areas of interest such as veteran fishers with experience in using certain fishing gears within a fishing and information sharing network. Indeed, conservation practitioners and other policy makers often tend to engage with persons that are more active in specific social contexts when implementing participatory conservation programs at the local level (Nguyen et al 2017).

Network clustering: Clustered networks are often characterised by higher level of generalized exchange, enabling faster, more complete flow of information that allow for better sanctioning of social norms such as spread of moral behaviour and trust among individuals (Granovetter 1978, Levine & Kurzban 2006). Clustering may also serve to reduce competition and increase motivation to transfer of novel messages by minimizing bottlenecks that may result from the costliness of the transfer to the benefactor (Reagans & McEvily 2003). Indeed, network clustering and individual action has been cited as good predictors of the tendency to innovate in social systems (Levine & Kurzban 2006). Even in a social system where gaps emerge in a network due to absence or little communication between distinct clusters, work on structural holes has shown that brokers can connect other-wise disconnected clusters and reap substantial gains for themselves from their clustered structure (Burt 2004). The small world phenomenon (Travers & Milgram 1967) further turns on the fact that even when everybody is not connected to everybody else, the few ties that connect distinct clusters allow novel ideas to diffuse (Centola & Macy 2007, VanderWeele 2011). Existence of weak ties, which are more likely in sparse but closed networks, have indeed been found to be key in accessing and transfer of novel information (Granovetter 1983). The counter-intuitive finding on the negative effects of sparsity or gaps in networks (i.e. the opposite of closure) further underscores the important role of direct and indirect ties in diffusion processes within network clusters (Ahuja 2000).

However, while network clustering supports communication, cooperation, and trust in social systems, it can also create isolation, cut externalities, and eventually pose a special challenge to contagion, diffusion process, and behaviour change (Levine & Kurzban 2006). The tendency to congregate in homogenous clusters has been shown to undermine innovativeness and transfer of complex knowledge between clusters (Centola & Macy 2007, Levine & Kurzban 2006). Thus, network clustering can impede complex contagion processes between clusters (Granovetter 1983).

Contagion effect (social influence): Though behaviours and states diffuse through social networks, the nature of social influence or contagion effects can occur in several ways. For example, for many simple spreading processes (i.e., spreading of low risk strategies or information), one individual displaying the behaviour might be sufficient to persuade a susceptible neighbour to adopt (Hill et al 2010, Wejnert 2002). However, there are many instances where person-to-person influence may be ineffective to transfer other types of interventions such as the spread of complex knowledge, practises or technologies (Reagans & McEvily 2003). It has often been suggested that multiple or strong ties between individuals are required for successful transfer of complex contagions, i.e., diffusion processes where adoption is conditional on the decision of a fraction of direct peers (Centola & Macy 2007). This conclusion is found in many studies tying network clustering, behavioural outcomes, and diffusion of innovations (Centola 2018, Centola & Macy 2007, Levine & Kurzban 2006).

To explicitly capture individual‘s communication behaviour, I measured their social networks. In social-ecological settings, social networks are important in facilitating information and knowledge exchange in cases where different stakeholders have come together to manage a shared resource (Bodin & Crona 2009, Folke et al 2005). These networks can even supersede the existence of formal institutions for effective compliance and enforcement of environmental management strategies (Scholz & Wang 2006). Indeed, social networks have been shown to be important for conservation diffusion (Matous & Todo 2015), having direct implications for environmental outcomes (Barnes et al 2016). Respondents were specifically asked to name up to 10 individuals with whom they fished with or shared information with about fishing. These two relationships (fishing and information exchange about fishing) were deemed particularly important for the potential for coastal and marine conservation diffusion to occur at the local level given that majority of households depend primarily on fishing to support their livelihoods, and because fishing activities represent the primary behaviour conservation and resource management agencies target in conservation efforts. Respondents could list their crew members, fellow captains, or any other stakeholder they fished or shared information with about fishing. I used recall methods (Marsden 1990, Wasserman & Faust 1994), where each respondent reported his relations. My entire analysis is based on weighted network ties. Attaching some form of weight to ties rather than analysing only their presence and absence allows more complex relational states between nodes to be captured (Opsahl et al 2010). Thus, I assigned a weight of [1] for information sharing ties, [2] for fishing ties, and [3] for ties associated with both fishing and information sharing. Information or knowledge sharing ties are clearly important for developing a common understanding of natural resources and bringing in new ideas (Watts & Strogatz 1998). However, fishing ties were assigned a higher weight due to their critical role in sharing practical experiences in fishing, which is essential to the adoption of fishing related technologies (Bodin & Crona 2009). Where a fishing and information tie was present, it was assigned an even higher weight due to key informants claiming such overlap captures the strongest, most intimate social relations in these traditional close-knit communities, where fishing is commonly undertaken by individuals with higher levels of trust among them (Bodin et al 2006, Bodin & Crona 2008).

Chapter 3: Factors that influence adoption and diffusion of conservation interventions

Synopsis

A critical gap in conservation diffusion is understanding the effect of social networks in adoption and diffusion processes. Here, I use emerging tools in network science to provide a novel examination of the combined effect of social networks and social influence (contagion) on conservation diffusion while accounting for key socioeconomic factors. I tracked adoption trajectories among fishers (n = 186) over time (i.e., a diffusion process) in four study sites. My results show that network processes contribute considerably to conservation diffusion – particularly in the early adoption stage – even when important socioeconomic factors such as knowledge of the innovation and risk orientation are accounted for. Equally striking, my results provide evidence that the provision of incentives does not promote early adoption, and actually contributes to non-adoption; suggesting that incentives may be counterproductive in some conservation diffusion processes. By showing that communication behaviour is crucial during the early stages of the diffusion process, my results challenge decades of diffusion research suggesting communication behaviour is more important for late adoption. For policy makers that are eager to achieve global sustainability outcomes, my results suggest that harnessing the power and characteristics of social networks may help jumpstart conservation diffusion through target populations.

Introduction

Many conservation interventions attempt to introduce novel ideas, technologies, or practices to stem ecosystem degradation, but can only be effective if they are adopted (Giller et al 2009, Weeks et al 2010). Lessons from the diffusion of innovations theory can provide a deeper understanding of the factors that enable (or inhibit) the adoption and spread of conservation initiatives (Rogers 2010). The diffusion of innovations theory argues that peoples‘ adoption behaviour is influenced by social differentiations in terms of personal attributes, socioeconomic status, and communication behaviour (Lublóy et al 2018, Mahler & Rogers 1999, Stoneman 1976).

To date, considerable research has affirmed the important role of personal attributes and socioeconomic status on the adoption of conservation interventions (Barham et al 2004, Diederen et al 2003, Knowler & Bradshaw 2007), yet there remains very limited empirical work emphasizing the effect of communication behaviour in this context (Matous & Todo 2015). Moreover, the majority of work that has been done in this area has been limited by the use of proxies of communication behaviour such as social participation, contact with change agents, and exposure to mass media (Fuglie & Kascak 2001, Läpple & Van Rensburg 2011). These proxies inherently ignore critical relational structures that more accurately capture how people access information and the embeddedness of individuals in social systems that can influence their adoption behaviour, e.g., through social influence (Barnes et al 2016, Valente 2012).

In the diffusion literature, consensus has emerged that a more robust way to explicitly capture people‘s communication behaviour is by assessing their social networks (Muller & Peres 2018, Valente 2010). The study of social networks is theoretically grounded in the notion that individuals are embedded within a larger context of relational ties (Borgatti et al 2009), and thus their behaviour is to some extent socially constructed as an outcome of their relationships with others (Fujimoto & Valente 2012, Valente 1996c). Thus, network analyses de-emphasize the analytical focus on solely individuals and instead focus on the network itself, while concentrating on it as a set of asymmetric ties binding individuals together (Warriner & Moul 1992). Network analysis therefore emphasizes the influences of social structure on decision-making over individualistic, cognate decision-making (Valente 1996c, Valente 2012).

Calls for using network processes in studying conservation diffusion have been accompanied by methodological guidelines (Cohen et al 2012, Matous & Todo 2015, Pietri et al 2009), but empirical studies are rare and results have often been inconclusive. The few attempts that integrate social networks in conservation diffusion are mostly limited to diffusion of conservation information (Pietri et al 2009, Ramirez-Sanchez 2011a, Ramirez-Sanchez 2011b), yet conservation interventions can be incredibly diverse ranging from information based conservation strategies to complex initiatives that seek behaviour change (Mbaru & Barnes 2017). To my knowledge, only one study uses network processes to study how conservation diffuses beyond information based conservation strategies (Warriner & Moul 1992). However, authors investigate network processes and socioeconomic characteristics separately, and therefore fail to account for the independent effects of social network position, network structures, and social influence (contagion) (Lusher et al 2013).

Social network position can have important influence on behaviour change especially on people that maintain numerous connections with many others or actors who are in positions that are different from them (Gladwell 2006). Network structures such as social enclaves or clusters can enable faster, more complete flow of information and resources, potentially allowing for rapid sanctioning of behaviour change among individuals (Granovetter 1978, Levine & Kurzban 2006). Social influence is a type of contagion effect on people‘s behaviour through social ties and association, which can translate into a wide variety of favourable outcomes, spanning social obligations such as adoption of new ideas, practise, and technologies (VanderWeele 2011). Importantly, these network properties can influence behaviour change, e.g., adoption of high-risk conservation interventions independently of other socioeconomic characteristics (Lusher et al 2013).

Here, I leverage recent advances in network modelling to simultaneously test the effect of social network position, network structures, and social influence on conservation diffusion while accounting for personal and socioeconomic status attributes. Given that diffusion research has shown that not all individuals in a social system adopt innovations at the same time, I describe the characteristics of key adopter categories at different stages along the diffusion curve (Fig. 1b). These are early adopters, late adopters, non-adopters, and one that is often overlooked, dis-adopters (those that adopt initially, but later abandon the intervention) (Barham et al 2004). The research aimed to find answers to the following specific research questions: What role do social networks play on adoption behaviour over the diffusion process? Are there differences in the effect of important determinants on adoption over time?

Methods

Survey design

This study was conducted in four landing sites where the conservation intervention was rolled out (i.e., site B, C, D, F in Fig. 4). Within experiments, research was coupled with the conservation program in order to track the diffusion process between January 2016 and January 2018. Tracking individuals over time allowed the diffusion process to be recorded in real time. This analysis therefore makes use of panel data comprising responses to the same questions by the same participants over time. captured by the seven gear types analysed, 49 in site C, 36 in site D, and 42 in site F; comprising a total sample of 186.

Predictor variables

In terms of personality traits, I included agency and risk orientation (Table 3). To capture socioeconomic status, I included education (maximum grade completed in formal education), material style of life (MSL, an indicator of wealth based on household possessions and house structure), occupational multiplicity (total number of different occupations), and formal leadership (whether or not one is a Beach Management Unit or other community leader). A proxy denoting the number of traps owned by a fisher describes the influence of size of firm (Feder 1980). Knowledge of the innovation (whether or not one had principle knowledge of the innovation before it was rolled out) was considered a proxy for conservation awareness. Age (age of the fisher), a key sociodemographic variable was included because of its relationship with other socioeconomic attributes such as work experience (Tiwari et al 2008). As mentioned previously, I had a handful of instances where some fishers were given the innovation to carry out experimental fishing with the new gear (provision of incentives). Therefore, I also included ‗provision of incentives' as an indicator variable to predict one's own adoption (defined here as a fisher physically modifying at least one of their own fishing traps to include the escape slot) (Table 4).

Social networks

This analysis makes use of undirected, weighted networks based on fishing and information-sharing ties. The use of undirected network ties was informed by the fact that a vast majority of the nominees in the networks were fellow crew members and captains who would ordinarily have a two way flow of communication. Each respondent was asked to name up to 10 individuals with whom they fished with or exchanged important information with about fishing (Chapter 2).

Table 4. Descriptive statistics for the socioeconomic predictors of adoption. Description of attributes as in Table 3.

Attribute	Statistic	Early	Late	Non-adopters	Dis-adopters[a]
	Sample (n)	53	51	82	16
Agency	Mean±SD	0.4±1.5	-0.2±0.5	0.1±0.9	-0.2±0.8
	Min	-0.5	-0.5	-0.5	-0.5
	Max	6.3	2.7	3.6	0.06
Risk orientation	Mean±SD	0.2±1.1	-0.1±1.0	0.1±1.0	-0.2±1.1
	Min	-1.6	-1.6	-1.6	-1.6
	Max	1.6	1.6	1.6	1.4
Formal leadership	Leaders	12(22.7%)	6(11.8%)	11(13.5%)	4(25%)
Material style of life	Mean±SD	-0.2±0.9	-0.4±0.8	-0.2±1	0.1±1
	Min	-1	-1	-1	-1
	Max	3.3	2.3	4.3	2.1
Occupation multiplicity	Mean±SD	2.4±0.8	2.7±0.9	2.3±0.9	2.3±1
	Min	1	1	1	1
	Max	3	4	4	4
Education	Mean±SD	4.4±3.8	4.5±3.5	5±3.3	4.8±4.1
	Min	0	0	0	0
	Max	12	10	12	12
Innovation knowledge	Mean±SD	0.3±1	0.5±0.9	-0.1±1.1	0.4±0.9
	Min	-1.1	-1.1	-1.1	-1.1
	Max	1.3	1.3	1.3	1.3
Provision of incentives	Provided	7(13.2%)	10(19.6%)	39(47.5%)	6(37.5%)

NB: summary statistics are presented for socioeconomic factors that showed significant association with adoption, non-adoption, or dis-adoption. [a] = the total does not add up to 186 because of some double counting with dis-adoption.

Network data was collected in three time periods, i.e., time one = before the innovation was rolled out (baseline surveys), time two = one year after the innovation was launched (first follow-up surveys), and time three = two years after the launch of the project (second follow-up surveys). During the first follow-up surveys, I surveyed some additional fishers (27) that had adopted the innovation but were not surveyed during my baseline surveys. No new adopters were recorded during the last sampling period. For this analysis, I therefore used network data from the first follow-up surveys because all participants were surveyed (i.e., adopters and potential adopters). I confirmed that the social networks measured did not exhibit substantial change over the three sampling periods using the RV coefficient (Robert & Escoufier 1976) (all coefficients were significant at 1%; Table A1). This coefficient is widely used to measure the closeness of two set of points represented in a matrix as well as test relationships between two sets of variables defined for the same individuals (Josse et al 2008, Schlich 1996). Results showed significant association between my adjacency matrices, suggesting that my networks did not change much over the three sampling periods at the site level (Table A1).

Analysis

I present a classic comparison widely applied in the diffusion literature that distinguishes between early and late adopters (Diederen et al 2003, Läpple & Van Rensburg 2011). Specifically, I considered innovators, early adopters, and the early majority collectively as *„early adopters"*; and the late majority and laggards collectively as *„late adopters"* (Fig. 1). I used the Autologistic Actor Attribute Model (ALAAM) to simultaneously test the effect of socioeconomic factors as well as social networks in the diffusion process (Wang et al 2014). ALAAM is a social influence model that was specifically developed to model contagion (social influence) and diffusion processes in which a network tie between two actors entails interdependent actor attributes (Lusher et al 2013). ALAAM assumes that network ties are fixed and that an individual's attribute of interest (i.e., adoption) may vary depending on the number of ties the individual has or on the corresponding attribute of others to whom the individual is connected.

Mechanics of the Autologistic Actor Attribute Model (ALAAM)

ALAAM is a social influence model that test how individual behaviour is influenced by the position in a social network and by behaviour of other actors in the network (Lusher et al 2013). When modelling behaviour of the actors, network ties are taken to be exogenous and cannot be changed by the attributes. I demonstrate the validity of this assumption using the RV coefficient by testing the association between my adjacency matrices over the three sampling periods at the site level (see appendix, Table A1). An attribute is regarded as a dependent stochastic variable measured at the level of an individual and a network tie variable is regarded as an independent fixed variable measured at the level of the dyad. The starting point for model development is the idea that the attribute of one individual is potentially dependent on and may potentially influence the attributes of others. Adoption being my outcome variable, the mechanics of the model was expressed in the following equations:

First, I considered a stochastic binary attribute vector Y = $[Y_i]$ where $i = 1,\ldots,n.$ which denotes adoption of the intervention. A realization (observed vector of attributes) of the stochastic vector Y is denoted by $y = [y_i]$ where $y_i = 1$ if early-, late-, or non-adoption is present. $y_{\mathrm{i}} = 0$ denote otherwise. I then considered a collection of network tie variables represented by a weighted matrix, where $x_{ij} = 1$ if information sharing tie is present, $x_{ij} = 2$, fishing tie is present, $x_{ij} = 3$ if tie is associated with both fishing and information sharing, and $x_{ij} = 0$ otherwise. All other binary or continuous covariates (predictors) attributes are denoted by $w = [w_i]$. With network ties treated as exogenous, (i.e., explanatory) network based social influence effects were inferred when i's attributes associated with the attributes of the actors who may have social relations with i through the network ties. The model makes one assumption that the probability of an attribute being present depends on the presence of the attributes in some local network neighbourhood of the actor. In this regard, it is possible that i may adopt a behaviour solely based on i's position in the network such as greater popularity or activity or because of other attributes of i. I specified a probability for observing the attribute for each possible observation as follows:

$$\Pr(Y = y|X = x) = \frac{1}{k(\theta_I)} exp\left\{\sum_{I} \theta_I z_I(y, x, \omega)\right\}$$

Where θi and Zi are parameters and statistics for network attribute configurations involving an interaction of dependent attribute (y), network (x), and covariate (ω) variables. The proposed model predict outcome variable Y while taking the network dependences between observations into account in a principled way that cannot be addressed in the standard logistic regression (Kashima et al 2013).

Before running the ALAAM, I combined all four networks from my four sampling sites effectively treating each network as a binary dummy variable. Because this step assumes homogenous effects across all four networks, I ascertained this homogeneity by performing chi-square goodness of fit (GOF) tests for the combined network and then used the same set of parameter values to rerun GOF for each network separately. The GOF statistics from the model networks were compared against simulated graph statistics based on 1000 samples, a million iterations, with a 100000 burn-in point. T-ratios were all smaller than 2.0 standard deviation units from the mean suggesting that the GOF statistics fit in all four individual networks separately (Wang et al 2014).

Modelling procedure

Social influence models such as the ALAAMs are highly sensitive and can easily be over parameterized (i.e., by having more predictors than can be estimated from the network data) (Wang et al 2014). I therefore adopted a two-stage process in order to narrow down the number of predictor variables. Stage 1 examined the personal attributes and socioeconomic status influencing early and late adoption decisions using a standard multinomial logistic model (Diederen et al 2003). The determinants associated with each category were contrasted with the base category, which is non-adoption (see Läpple and Van Rensburg (2011) for a detailed illustration of this procedure). Individual covariates that significantly influenced early and late adoption were included as covariates for individual level predictors in the ALAAM model. Individual covariates that significantly influenced early and late adoption were included as covariates for individual level predictors in the ALAAM model. In the initial multinomial procedure, I included ten important socioeconomic attributes as predictors: age, agency, formal leadership, innovation knowledge, education, material style of life, risk orientation, occupational multiplicity, number of traps, and provision of incentives. An examination of variance inflation factors indicated there was no sign of multicollinearity among these socioeconomic variables (Fox & Weisberg 2011). Site was included as a random factor to account for potential differences across sites.

Stage 2 involved using the ALAAM to test the combined effect of personal attributes, socioeconomic status, and social networks on adoption. Using early-, late-, and non-adopters as outcome variables, I tested for the personal attributes and socioeconomic status that were significant in the multinomial model, plus five key network effects that have been widely used to model behaviour in social networks.

(1) Popularity (actor activity) - testing whether actors who were generally more popular in the network were more likely to adopt the intervention (Table 5). By definition, popular actors tend to maintain many more times the number of ties than the average person does (Valente et al 2008). Because of their ability to connect directly to many others, popular actors are more likely to access novel information more quickly especially when ties are linked to other actors in positions or hierarchical levels that are different from them (Gladwell 2006). Depending on the information gained, these generalized exchanges can allow rapid transfer of new ideas and practises or result in changes in behaviour among individuals (Valente 1996c).

(2) Activity (actor 2-star) - this is an indicator that can be used to check whether actors who were generally more active in the network and had multiple network partners were more likely to adopt (Table 5). Actors that are more active in a network tend to maintain ties with other actors for the benefit of receiving or giving specific information (i.e., information gatherers and disseminators) that is solely associated with the type of social network in context (Lusher et al 2013). Though network studies does not argue this explicitly, their description of active actors suggests that actors who are generally more active in a given network can be specialized in areas of expertise covered in the network questions (Lusher et al 2013). For example, in fisheries social-ecological settings where fishing is characterized by a multiplicity of gears, species, and vessels with various capacities there can be many active actors in particular areas of interest such as veteran fishers with experience in using certain fishing gears within a fishing and information sharing network.

(3) Clustering (actor triangle) – I included a network clustering effect to examine whether adoption of the intervention is associated with clustered regions of the network (Table 5). Network clustering is considered one of the most important predictor of diffusion processes in classical networks because clustering is often associated with trust, cooperation, and more

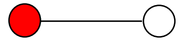
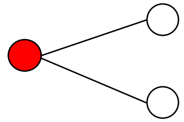
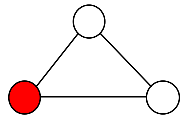
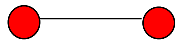
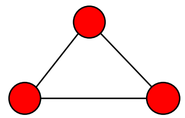
complete flow of information in social systems (Centola 2018, Hansen 1999). Indeed, network clustering is often associated with better transfer of complex contagions, e.g., adoption of unproven high risk innovations (Centola & Macy 2007, VanderWeele 2011).

(4) Partner attribute contagion (direct social influence) – this is a network contagion effect that tests whether adoption can be associated with direct social influence between two socially connected actors (Table 5). (5) Partner – partner attribute triangle (contagion within groups) - I looked at direct social influence within clustered regions of the network (partner attribute triangle) to ascertain whether adoption was associated with contagion within groups (Lusher et al 2013) (Table 5).

Diffusion processes through social networks can occur between person-to-person (i.e., direct social influence), by multiple or strong ties between individuals, or by social cohesion (i.e., third-party ties around relationships) (Reagans & McEvily 2003). It is often argued that in cases where node-to-node social influence is infective to transfer certain types of interventions such as the spread of complex knowledge, practises, or technologies social cohesion can facilitate transfer of complex contagion processes among social systems (Ahuja 2000). Cohesive groups tend to congregate homogenous actors thereby decreasing the impediments associated with node-to-node social influence (Reagans & McEvily 2003). (6) attribute density was included as an intercept term to show if the outcome variable can be observed in the network (Lusher et al 2013).

To describe dependencies on the observed network and individuals‘ covariates (nodal attributes), I ran exponential random graph models (ERGMs) (Lusher et al 2013). Here, I checked for activity and homophily on the observed network on all indicator variables, controlling for different network configurations (appendix, Table A2).

Table 5. Description of network and actor attributes effects.

Parameter	Interpretation	Configuration
Network position		
Density	Baseline probability of the attribute, i.e. adoption of the intervention, being present.	
Actor activity (popularity)	Actors who are generally more popular in the network are more likely to adopt the intervention.	
Actor 2 star (activity)	Actors who are generally more active in the network and have multiple network partners are more likely to adopt the intervention.	
Actor triangle (network clustering)	Adoption of the intervention is associated with clustered regions of the network.	
Network attribute		
Partner attribute contagion (direct social influence)	Network contagion effect (direct social influence among two socially connected actors).	
Partner – partner attribute triangle (contagion within groups)	Adoption of the intervention is associated with contagion within groups (direct social influence within clustered regions of the network).	

 actors who have adopted the intervention  other actors (who have or have not adopted the intervention)

Statistical results for the ERGMs indicate whether any of the attributes in the ALAAM model significantly drove tie formation in the network (Table A2). Multinomial approaches are unable to predict dis-adoption due to its overlap with other adoption categories, i.e., dis-adopters are also early, late, or laggard adopters (Barham et al 2004).

In order to examine which socioeconomic characteristics most strongly predict whether an individual is likely to be a dis-adopter, I employed a logistic regression model. Due to the relatively small number of fishers that gave up the practice (n = 16) relative to the sample size (186) and large number of potentially relevant indicators (10), I used a rare events logistic regression (RELOGIT) model for dichotomous dependent variables (Westland, 2010). The RELOGIT procedure estimates the same model as a standard logistic regression, but the estimates are corrected for the bias that occurs when the sample is small or the observed events are rare; i.e., if the dependent variable has many more 1s than 0s, or the reverse. To examine the differences between dis-adopters and the other adopter groups (i.e., adopters = early and late adopters, and non-adopters), I used independent samples tests, based on the ten socioeconomic attributes. I was also unable to perform the ALAAM for dis-adopters because only a small number (16) gave up the practise.

To capture differences in network properties between dis-adopters and those that maintained the innovation (i.e., adopters = early and late adopters) and non-adopters, I performed independent sample tests comparisons on the basis of four centrality metrics that capture different types of prominence or influence as highlighted in network theory (Freeman 1978, Valente 1996c). I looked at closeness centrality (Newman 2010, Rochat 2009), betweenness centrality (Freeman 1978), degree centrality (Wasserman & Faust 1994), and eigenvector centrality (Bonacich 1972). Closeness centrality takes into account how close an actor is located to all other actors in a network (Gil-Mendieta & Schmidt 1996) and is therefore associated with actors who can receive or send information to all actors in a network quickly and efficiently (Costenbader & Valente 2003). Betweenness centrality identifies actors who sit between many other actors in a social network (Butts 2008) who can therefore act as transmitters of resources and information between disconnected actors (Barnes-Mauthe et al 2015, Borgatti et al 1998). Degree centrality measures the number of direct ties an actor has, and has been positively related to trust (Freeman 1978, Tsai & Ghoshal 1998) and influence in social networks (Valente et al 2008). Eigenvector centrality measures the extent to which actors are connected to others who are themselves well connected, thus affording them with a globally central position in a network (Bonacich 1972, Butts 2008). Depending on the information extracted from their social world, most central nodes or actors can obtain substantial benefits that can lead to a number of behavioural outcomes such as uptake of innovative ideas and practises (Valente 1996c). To visualize the networks and show the position of early, late, non-adopters, and dis-adopters in the networks, relational matrices based on reported fishing and information sharing ties were created and plotted in Visone (Baur et al 2001) by an algorithm that uses iterative fitting on a force-directed layout.

Sensitivity analysis

To determine whether my results are robust to the extent of using weighted ties, I reran all analyses using binarized network ties. Results from this sensitivity analysis did not change much from those using weighted ties. The only notable difference is that risk orientation turned out to be positively related to early adoption when binarized ties were used whereas no relationship existed between risk orientation and adoption when weighted ties were used. The rest of the results remained the same. This is not surprising because only a handful of nominees were non fishers in the networks - a situation that ensured a vast majority of the ties between nominees and respondents followed the same pattern in the two networks.

Results

Of the 186 respondents, early adopters account for 28.5%, whereas late adopters and non-adopters are represented by 27.4% and 44.1% of the sample, respectively (Table 4). Results from an initial multinomial regression model including the full range of socioeconomic and personal attributes identified as important for adoption in existing research show that when social networks are not accounted for, early adoption is related to education, risk orientation, and knowledge of the innovation; while late adoption is related to occupational multiplicity and the provision of incentives (Table A3). These five socioeconomic attributes (education, risk orientation, knowledge of the innovation, occupational multiplicity, and provision of incentives) were therefore included as covariates in our social network model (Table 5), discussed in the following paragraph.

Examining the combined effects of personal attributes, socioeconomic status, and social networks on adoption, I find a range of important network effects (Table 6). First, the general level of social connectivity (popularity), connections with numerous partners that are active in the network (activity), and clustering (actor triangle) have significant effects on early adoption. Specifically, a positive significant popularity parameter ($\beta = 0.52$, $p < 0.05$) suggests that fishers with multiple ties are more likely to be early adopters (Table A4). Early adoption also appears to be dependent on the number of active network partners within the fishing and information sharing network a fisher has given the positive and significant activity parameter ($\beta = 0.11$, $p < 0.05$). The positive significant parameter for clustering ($\beta = 0.53$, $p < 0.05$) shows that nodes in clustered regions of the network (i.e., where there are strong, cohesive groups of interconnected people) are also more likely to adopt early. There was no direct social influence effect, which means that given other model parameters, having one network contact who adopts does not appear to significantly affect one's chances of adoption. However, I found a positive effect of social influence within groups ($\beta = 1.3$, $p <$

0.05), showing that exposure to multiple adopters in clustered regions of the network increases one‘s probability of being an early adopter. For non-adoption, a negative and significant popularity parameter (β = -0.73, $p < 0.05$) suggests that fishers with fewer ties are less likely to adopt the innovation. There were no significant social network effects associated with late adoption other than the density parameter, which confirms that late adoption was observed in the network (Table 6).

Only innovation knowledge, provision of incentives, and occupational multiplicity emerged as important socioeconomic predictors of adoption behaviour when social network effects were taken into account (Table 6, Table A4). Precisely, I found that having knowledge of the innovation (β = 0.32, $p < 0.05$) was likely to increase ones chances of becoming an early adopter. Having multiple occupations (occupational multiplicity; β = 0.36, $p < 0.05$) and the provision of incentives (β = 0.8, $p < 0.05$) had a significant positive effect on late adoption. Innovation knowledge also had a significant negative relationship with non-adoption (β = -0.12, $p < 0.05$). The provision of incentives was also positively related to non-adoption (β = 0.75, $p < 0.05$; Table 6, Table A4).

About a quarter (24.5%) of those who had adopted the practice late ended up abandoning it (i.e., became ‗dis-adopters'), compared to only 5.9% of early adopters (Table 4). This means late adopters were more likely to dis-adopt than early adopters. Nearly half (47.5%) of those provided with incentives did not end up adopting the practice (i.e. modifying their own traps); while 13% of early adopters and 20% of late adopters were provided with incentives (i.e., initially given the innovation) (Table 4). Dis-adopters have a significantly higher closeness centrality (i.e., t = -2.18 when compared to adopters, and t = -1.48 when compared to non-adopters) (Table 7). No significant differences in degree, betweenness, and eigenvector centrality were detected between dis-adopters and the other groups.

Table 6. Factors that influence adoption at different stages. Results of Auto-logistic actor attribute model (ALAAM) for the adopter groups. RELOGIT procedure was used for dis-adopters.

	Attributes	**Early adopters**	**Late adopters**	**Non-adopters**	**Dis-adopters[a]**
Network effects	Density	(-)	(-)	(+)	-----
	Popularity	(+)		(-)	-----
	Direct social influence				-----
	Activity	(+)			-----
	Network clustering	(+)			-----
	Contagion within groups	(+)			-----
Socioeconomic factors	Agency	-----	-----	-----	(-)
	Risk orientation	(+)[b]	-----		-----
	Formal leadership	-----	-----	-----	(-)
	Material style of life	-----	-----	-----	(+)
	Occupation multiplicity	-----	(+)		-----
	Education		-----		-----
	Innovation knowledge	(+)	-----	(-)	-----
	Provision of incentives		(+)	(+)	-----

KEY: Number of observations = 186; (+) = positive significant effect; (-) = negative significant effect; ----- = No tests performed; [a] = RELOGIT regression model. [b] = risk orientation came out as significant for early adopters when binarized ties were used. Other results did not change.

Table 7. Factors that distinguish dis-adopters from other adopter groups; i.e., all adopters (early and late) and non-adopters.

Attributes	Dis-adopters vs. all adopters				Dis-adopters vs. non-adopters			
	Test statistic	Standard error	95% Confidence Interval		Test statistic	Standard error	95% Confidence Interval	
Closeness centrality	t = -2.18**	0.04	-0.17	0.01	t = -1.48*	0.05	-0.17	0.03
Agency	t = 2.38*	0.02	-0.08	0.01	t = 11.75**	0.09	-0.29	0.05
Risk orientation	t = 0.11	0.14	-0.24	0.29	t = 0.41	0.13	-0.22	0.31
Formal leadership	$\chi2$ = 2.57	0.11	-0.3	0.12	$\chi2$ = 4.48**	0.1	-0.32	0.08
Material style of life	t = -1.76**	0.25	-0.96	0.09	t = -0.76	0.27	-0.73	0.33
Occupation multiplicity	t = 1.14*	0.22	-0.19	0.69	t = 0.14	0.23	-0.43	0.49
Education	t = -0.38	1.09	-2.67	1.86	t = 0.18	0.94	-1.69	2.02
Innovation knowledge	t = -0.08	0.25	-0.54	0.5	t = -1.54**	0.27	-0.95	0.13

T-tests were used for interval variables, whereas chi-square tests were used for categorical variables. *p < 0.05; **p < 0.01

In terms of socioeconomic status and personal attributes, I found that dis-adopters had lower levels of agency compared to both adopters ($t = 2.38$) and non-adopters ($t = 11.75$) (Table 7). Further, compared to other adopters who retained the innovation, dis-adopters had higher levels of material wealth ($t = -1.76$) but lower occupational multiplicity ($t = 1.14$; Table 7). Compared to non-adopters, dis-adopters had more knowledge of the innovation ($t = -1.54$) and were less likely to be formal leaders ($\chi^2 = 4.48$). Respondent's age and the number of traps they used were not related to adoption or dis-adoption (Table 7; Table A3).

Summary statistics of all predictor variables are reported in Table A2. Basic network characteristics are presented in Table A5 along with other network attributes. The networks exhibit small world properties, with an average network path length of between 4.1 to 5.2, and a graph clustering rate of 10 - 16% (Table A5). This means that the ratio of the number of closed triples (actors in groups) to the number of two-stars (actors that are more active but not in groups) is just over a sixth, indicating that the network graphs are somewhat clustered (Banerjee et al 2013). Gear ownership turned out to be a redundant parameter because all fishers owned their traps and therefore not presented.

Discussion

This study provides a novel examination of key factors related to conservation diffusion. I employ emerging tools in network analysis that are specifically designed to capture social influence and diffusion processes while accounting for socioeconomic factors (i.e., personal attributes and socioeconomic status) of individuals in social systems (Lusher et al 2013). Unlike previous conservation diffusion studies (Fuglie & Kascak 2001, Mascia & Mills 2018), I show that adoption is not only linked to personal and socioeconomic status attributes, but also shaped by complex social relations and the actions of others. Overall, my results show that network processes contribute considerably to adoption – particularly during the early stages of the diffusion process. Indeed, I show that even general levels of connectivity (i.e., popularity) in a network can be important for early adoption. By showing that adoption behaviour is associated with the corresponding adoption status of the network partners (i.e., network clustering), my analysis confirms the existence of independent effects of social connectivity and spillover between individuals on conservation adoption behaviour. I did not find a direct node-to-node network contagion effect (i.e., direct social influence); instead, I show that the adoption status of network partners in strong cohesive groups has significant effects on early adoption. Taken together, these results demonstrate that harnessing the power and characteristics of social networks can help obtain the critical mass needed to accelerate conservation diffusion processes through target populations. I discuss my findings and their implications in greater detail below.

Within localized social structures, my analysis shows that adoption is more pronounced in clustered regions of the networks. Precisely, I show a positive effect of network clustering for early adopters, indicating that clustering, often associated with social consolidation of shared norms and practices (Centola & Baronchelli 2015), can contribute to adoption. This means that in this case, only special forms of social influence (i.e., network ties within groups) appear to effect the successful diffusion of complex conservation innovations. In the current context, this finding indicate that localized enclaves may be more efficient as critical injection points for participatory conservation programs. Targeting individuals in distinct social subgroups could therefore help amplify the initial effect of localized conservation interventions at the community level as opposed to spreading resources more broadly. This conclusion is supported by many studies tying network clustering and innovation to transfer highlighting that multiple or strong ties between individuals in cohesive subgroups may reduce competition (Centola & Macy 2007, Opsahl 2013), minimize bottlenecks and costs associated with innovation transfer (Burt 2004), as well as decrease the impediments associated with node-to-node social influence (Reagans & McEvily 2003).

By integrating social networks in the longitudinal analysis of conservation diffusion, I highlight key additional findings that are equally striking. Foremost, by showing that communication behaviour is key during early stages of the diffusion process, my results seem to challenge decades of diffusion research that suggest communication behaviour is more important for late adoption (Diederen et al 2003, Rogers 2004). By showing there are minimal differences in terms of personal attributes and socioeconomic status between early and late adopters, my study also challenges the longstanding notion that a wide range of different socioeconomic factors affect early vs. late adoption (Diederen et al 2003, Läpple & Van Rensburg 2011). Effectively my results therefore suggest that the range of socioeconomic attributes distinguishing early from late adopters may not be as broad as previously thought once social network characteristics are taken into account. Two key observations can possibly explain this result. Firstly, my research explicitly measured communication behaviour rather than rely on proxies, which has largely been relied on in previous research. Secondly, this study focused on fishers who are known to display peculiar attributes (e.g., they tend to exhibit more risk seeking behaviour) that are not representative of the general population (Cinner et al 2010). Thus, despite the large sample size across different locations, the findings might be specific to this particular intervention and the social-ecological setting and should therefore be generalized with care.

Though my results indicate social networks are incredibly important for conservation diffusion, I found that a handful of key socioeconomic factors can also play a role. Specifically, knowledge of the innovation was a strong characteristic of early adopters, whereas a lack of such knowledge hindered adoption altogether. This finding emphasises the need for periodic and more sustained educational and awareness campaigns to provide local people with necessary knowledge about conservation interventions. Knowing about the existence of a conservation intervention is a critical step in the adoption decision process because no adoption can occur without initial knowledge (Lynne et al 1995). Indeed, having proper knowledge of a conservation innovation can reduce perceived risks and uncertainties associated with adoption (Feder & Slade 1984, Marra et al 2003). Conservation practitioners with specialized knowledge of the conservation innovation can therefore increase their direct engagements with target communities to increase learning opportunities. In the present case, increased exchange of information and knowledge about the conservation innovation can translate into a better understanding of the long term objectives of achieving fisheries sustainability through the use of escape slot traps. This might eventually have a direct positive influence on adoption.

Providing incentives had no significant influence on early adoption behaviour although was important for late adoption and significantly contributed to non-adoption. Quite simply, people who were provided with escape slot traps were unlikely to acquire additional escape slot traps. These results have significant implications for conservation programs because they suggest that at worst, providing incentives may be counterproductive in some conservation diffusion processes; while at best, they are unlikely to induce an automatic shift towards the adoption of conservation initiatives. Incentives to adopt innovations or coercive pressure have previously been shown to shape people's perceptions that the innovation is both desirable and inevitable (Rogers 2010). Indeed, for conservation interventions that require huge investment capital or other costs associated with adoption, inadequate incentives has been highlighted as a major constraint to the rapid adoption of conservation interventions (Feder & Umali 1993, Knowler & Bradshaw 2007). Although the consensus stipulates that incentives can positively influence adoption behaviour - that was not the case in the present study. This findings seem to reinforce the argument that in societies where people are heavily dependent on aid, e.g., communities in but not limited to developing countries, offering incentives can undermine conservation diffusion processes (Eliasen et al 2013). To support this narrative, some scholars have argued that provision of incentives tend to create false hope (i.e., false sense of security built entirely around certain benefits that accrue but with no knowable chance of sustainability) – a scenario that often discourage investment in innovative practices over time (Eliasen et al 2013, Feder et al 1985, Läpple & Van Rensburg 2011).

The effect of material wealth in the conservation literature has elicited varied opinions in relation to elite capture and elite control (Dasgupta & Beard 2007, Ribot 2002). It is assumed that wealthy persons are more likely to encourage investment in conservation practices given their greater capacity to deal with potential setbacks (Amsalu & De Graaff 2007). Conversely, it has been argued that unfavourable opinions or experiences about conservation that seeks behaviour change from wealthy persons could potentially undermine conservation efforts given the power and influence that they might have over less privileged individuals in rural settings (Mbaru & Barnes 2017). Here, I show a direct positive relationship between material style of life and fishers that abandoned the innovation after sometime. Interestingly, my results further show that higher closeness centrality is a unique characteristic of dis-adopters, suggesting that any unfavourable opinion about a given conservation practice from dis-adopters could, in theory, quickly and efficiently spread to other members of the network (Mbaru and Barnes 2017; (Costenbader & Valente 2003). Conversely, formal leadership was significantly associated with a lower probability of abandoning the innovation after adopting it. This indicates that formal leaders can help to solidify conservation innovations, and therefore may be good targets when rolling out innovations. Nonetheless, my results provide a cautionary tale suggesting that wealth, coupled with a lack of leadership responsibilities, may drive behavioural tendencies that could potentially reverse significant gains of conservation diffusion.

The sensitivity of early adopters and dis-adopters to personal attributes such as risk orientation and agency was observed only when social networks were discounted. These results support findings in a plethora of diffusion studies that show personal or attitudinal influences such as risk seeking, among other personality traits that revolve around rationality underlie attitudes towards new practices and therefore important in shaping adoption behaviour (Feder 1980, Mercer 2004). However, risk orientation in my case became less important on the part of early adopters when social networks were taken into account. This finding emphasizes the point that social interactions can play a major role in moderating risk perceptions on new ideas and practises, e.g., high risk unproven conservation technologies as the one studied here (Valente 1996c). I did not simultaneously test the relationship between dis-adoption and the three broad socioeconomic factors (i.e., social network, socioeconomic status, and personal attributes). Therefore, it remains to be seen whether social embeddedness can also offset attitudinal influences such as agency that might contribute to dis-adoption of conservation innovations. The decision to use of weighted ties had little influence on the modelling results, with the exception of risk orientation, which came out as significant when binary ties were used.

Concluding remarks

This study has highlighted key factors associated with adoption behaviour, which may expand our understanding of the wider considerations influencing uptake of complex conservation initiatives seeking behaviour change. Overall, my results suggest that social network processes can significantly influence conservation adoption behaviour independently of other socioeconomic characteristics. By utilizing the social network approach, my study moves beyond the conventional analysis of adoption behaviour to a more refined and robust approach that specifies further the relational basis of adoption. The long-standing notion that socioeconomic status and personal attributes are more important for early adoption while communication behaviour is more important for late adoption is challenged by my longitudinal analysis of a conservation diffusion process that explicitly accounts for social networks. For policy makers that are eager to achieve global sustainability outcomes, my results suggest that harnessing the power and characteristics of social networks can help diffuse conservation initiatives through target populations.

Chapter 4: Key players in conservation diffusion

Synopsis

Identifying the right stakeholders to engage with is fundamental to ensuring conservation information and initiatives diffuse through target populations. Yet this process can be challenging, particularly as practitioners and policy makers grapple with different conservation objectives and a diverse landscape of relevant stakeholders. Here I draw on social network theory and methods to develop guidelines for selecting ‗key players‘ better positioned to successfully implement four distinct conservation objectives: (1) rapid diffusion of conservation information, (2) diffusion between disconnected groups, (3) rapid diffusion of complex knowledge or initiatives, or (4) widespread diffusion of conservation information or initiatives over a longer time period. Using complete network data, I apply this approach to select key players for each type of conservation objective. I then draw on key informant interviews from seven resource management and conservation organizations working along the Kenyan coast to investigate whether the socioeconomic attributes of the key players I identified match the ones typically selected to facilitate conservation diffusion (i.e., ‗current players‘). My findings show clear discrepancies between current players and key players, highlighting missed opportunities for progressing more effective conservation diffusion. I conclude with specific criteria for selecting key stakeholders to facilitate each distinct conservation objective, thereby helping to mitigate the problem of stakeholder identification in ways that avoid blueprint approaches.

Introduction

Consensus has emerged on the need to involve intermediaries in diffusion processes (Gladwell 2006, Rogers 2010). This involvement not only facilitates uptake and transitory use of new ideas and practices but also fosters the two-way flow of information and knowledge about innovations (Gladwell 2006). In the conservation context, proper communication channels can foster long-term interest in conservation, promote local support, and propel the spread of novel conservation ideas and practices for effective governance of natural resources (Khataza et al 2018, Nguyen et al 2017, Young et al 2016). Identifying the right stakeholders that are optimally positioned to diffuse conservation information, knowledge, and practices can therefore be fundamental to successful conservation efforts in social-ecological systems (Armitage et al 2008, Ostrom 2007b). However, identifying these key individuals (also referred to as ‗opinion leaders' or ‗change agents') is becoming more complex as the landscape of stakeholders in social-ecological systems diversifies and practitioners and policy makers grapple with increasingly variable conservation objectives (Arias 2015, Bottrill et al 2008, Cohen et al 2012).

Communities are inter-sectoral social arenas with networks of social relations between different actors at various levels (Cohen et al 2012). These social networks are rarely homogeneous; rather, they are partitioned into complicated subgroups of individuals and stakeholders with different resources, interests, perceptions, affiliations and amounts of influence (Carlsson & Berkes 2005, Mertens et al 2005, Nygren 2005). In this context, certain people may be more effective than others at facilitating conservation diffusion due to their capability to pass information efficiently and rapidly to many others in the community (Beauchamp 1965, Valente & Davis 1999), their capability to control or coordinate the flow of information between disconnected communities (i.e., ‗brokers') (Valente et al 2008), or other factors related to their social-structural position. Despite this, to date, natural resource managers and conservation practitioners have consistently relied on local community leaders (hereinafter ‗leaders') to diffuse and implement conservation actions at the community level (Armitage et al 2008, McClanahan & Cinner 2008, Olsson et al 2004). Although these leaders can be socially embedded in social-ecological settings, they may not be better positioned to effective diffuse all types of conservation intervention and in some cases may struggle to deliver greater than localized conservation outcomes (Berkes 2004, Pajaro et al 2010).

Conservation initiatives can be incredibly diverse and they often have different reasons for seeking stakeholder involvement. Stakeholder involvement is often sought in order to facilitate diffusion and adoption (e.g., of information and behaviours), yet even still different types of stakeholders may be more important to involve depending on the specific conservation goal. For example, spreading of conservation information quickly is often necessary, especially when rapid awareness creation is needed to protect and safeguard certain species or habitats under emergency threat (Haddow et al 2013, Kapucu 2008). Social-ecological systems are also typically comprised of disjointed social structures, so there is often a need to identify brokers who can bridge conservation ideas and practices amongst disconnected groups (Barnes et al 2016). Conservation information can also be highly complex, and many initiatives specifically seek to implement behaviour change among various stakeholders. In such cases, engaging with highly influential stakeholders with many opportunities to influence others would be particularly ideal for widespread adoption to occur as quickly as possible. Finally, spreading conservation information widely and facilitating widespread adoption of more complex conservation initiatives over a longer time period is often necessary to achieve global sustainability outcomes (Mace 2014, Pannell et al 2006b).

Here, I draw on social network theory and methods to present guidelines for selecting key players optimally positioned to successfully implement four distinct diffusion-related conservation objectives. Social network analysis (SNA) is an analytical approach that can identify the social structures underpinning social-ecological systems and shed light on the positions of key stakeholders. In the context of conservation, scholars have applied SNA to better understand how social-structural factors relate to processes that facilitate successes and failures in resource management (Bodin & Crona 2009). Critically, social networks have been shown to be important for conservation diffusion (Matous & Todo 2015), having direct implications for environmental outcomes (Barnes et al 2016). In an effort to combat conflict, marginalization, and unfair representation of diverse interests in conservation, SNA has also been directly employed as a method for stakeholder analysis in order to select relevant stakeholders for participatory conservation initiatives (Prell et al 2009, Reed et al 2009). I expand upon this body of work by demonstrating how SNA can be applied to select key players most optimally placed to facilitate conservation diffusion.

Given the diversity of goals associated with conservation initiatives discussed above, I analyze four distinct diffusion-related conservation objectives: (1) rapid diffusion of conservation information; (2) brokering of conservation information and initiatives between disconnected or fragmented communities; (3) rapid diffusion of complex knowledge or conservation initiatives; and (4) widespread diffusion of conservation information or initiatives over a longer time period. I distinguish between spreading conservation information (simple spreading; typically associated with conservation objectives 1, 2, and 4) and complex knowledge or complex conservation initiatives (complex contagions; typically associated with conservation objectives 3) because the role of influential actors, the rate of spread, and the effects of network structure on spreading processes differ between the two (Granovetter 1978, Karsai et al 2014). Specifically, complex contagions processes (i.e., spreading of unproven technologies or high risk strategies) occur when the exposure of an individual is conditional on the decisions made by a fraction of his or her peers (Centola &

Macy 2007, Valente 1996c). In contrast, for simple spreading processes (i.e., spreading of low risk strategies or information), one ‗infected' neighbour is often sufficient to expose a susceptible individual for adoption or diffusion to occur (Hill et al 2010, Wejnert 2002).

It is foreseen that failure of participatory programs will remain as long as there is ineffective involvement of key stakeholders in the management of natural resources. This scenario therefore calls for a specific approach that determines how local stakeholders are involved and by whom amongst these stakeholders is involved in order to achieve successful outcomes in participatory approaches.

Drawing on social network theory, I begin by demonstrating how different conservation information and behaviours associated with the four objectives listed above can be expected to diffuse in a community, and provide guidelines for using SNA to identify key individuals to spearhead these conservation actions. I then empirically demonstrate how these guidelines can be used to identify key individuals to act as critical injection points in the diffusion of each conservation objective (i.e., key players) to show that different types of people are likely to be more effective depending on the conservation goal. Finally, I compare the types of individuals identified as key players for diffusion with the individuals that are currently selected for engagement by conservation organizations and resource management agencies (i.e., current players) to highlight missed opportunities for progressing more effective conservation diffusion. I accomplish this by leveraging comprehensive data on social networks and information on conservation diffusion strategies currently being applied along the Kenyan coast.

Identifying key stakeholders for specific conservation goals

A large body of work in sociology has demonstrated how actors' position in a social network determines how effective they are at acting as a conduit for the spread of information and whether or not they have the power to influence others either directly or indirectly (Freeman 1978, Valente 1996c). Based on their closeness to others, network position, level of connectedness, direct interactions, or nominations, certain well-connected individuals are typically referred to as ‗central' in social network theory (Freeman 1978, Valente 1996c). These central positions have often been equated with opinion leadership, change agency, prominence or popularity, all of which are associated with diffusion and adoption behaviours (Valente 1996a, Valente & Davis 1999). There are a range of different centrality metrics which emphasize different structural aspects of complex social systems. I focus on four: (1) closeness centrality (Newman 2010, Rochat 2009), (2) betweenness centrality (Freeman 1978), (3) degree centrality (Wasserman & Faust 1994), and (4) eigenvector centrality (Bonacich 1972); each of which captures different types of prominence or influence relevant for facilitating the four conservation objectives included here (see Table 8). I discuss these measures in turn.

Closeness centrality: This metric takes into account how close an actor is located to all other actors in a network (Gil-Mendieta & Schmidt 1996). Closeness centrality is important in identifying persons who are best positioned to spread novel information quickly and efficiently throughout a network (Costenbader & Valente 2003) – people who would therefore be most appropriate to efficiently transmit novel conservation ideas and information more quickly and rapidly to many others across a social-ecological system. Closeness centrality can be expressed as

$$C_i = \frac{\sum_j {d_{ij}}^{-1}}{n-1}$$

where d_{ij} is the shortest path (geodesic distance) between nodes i and j, i.e., sum of all geodesic distances from i to all others (Gil & Schmidt 1996). Computation for every node of the closeness centrality index however needs the distances between all pairs of vertices

(Rochat 2009). As such, where a graph is disconnected, the formula for computing closeness centrality described above can be useless because the distance between two vertices belonging to different components is infinite by convention. To correct this limitation, an alternative formula for computing closeness centrality was developed that replaced the infinite distance between two vertices belonging to two distinct components by the number of vertices of the graph: the largest geodesic possible in a graph with n vertices is of length n -1 (Rochat 2009). Thus for a disconnected graph, the formula changes as follows:

$$C_{\propto}(xi) = n = 1/\sum_{j\neq i} \mathrm{dist}(x_i, x_j) + m \propto$$

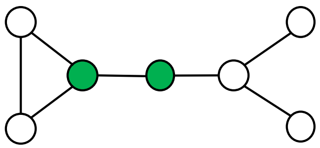
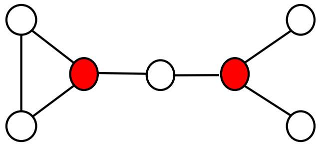
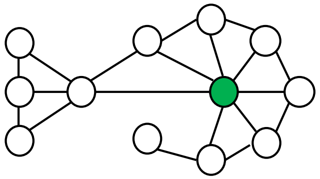
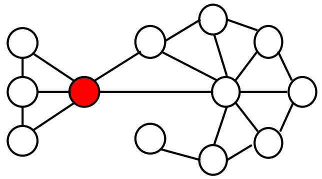
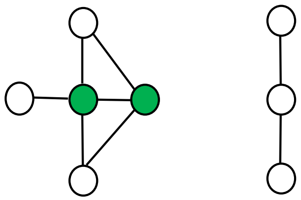
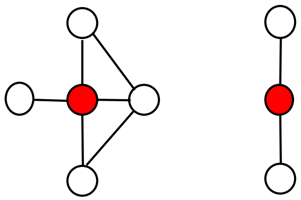
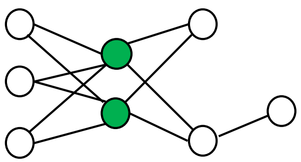
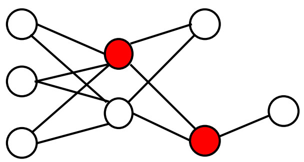
with $xi \in V$, V the set of nodes, $n = |V|$ and dist(x_i, x_j) the distance from node x_i to node x_j. Vertices $\{x_j\}_j$ chosen in the same connected component as the vertex x_i, $n = |V|$, m the number of vertices unconnected to x_i and $\propto \in R_+$ a constant greater than or equal to the diameter of graph (Rochat 2009).

Betweenness centrality: This measure identifies actors who sit between many other actors in a social network (Butts 2008) – people who are often referred to as ‗brokers'. The measure specifically identifies the extent to which a node falls between others on the shortest path length, thereby allowing it to act as transmitter of resources and information between disconnected actors (Barnes-Mauthe et al 2015, Borgatti et al 1998). Betweenness centrality is calculated as follows

$$B_i = \sum_{jk} \frac{g^i{}_{jk}}{g_{jk}}$$

where g_{jk} is the number of shortest paths between nodes j and k, and g^i_{jk} is the number of those paths that pass node i. In the case of $g_{jk} = 0$, the corresponding contribution to the betweenness score is zero (Butts, 2008).

Table 8. Hypothetical network diagrams depicting four centrality measures. Green represent node(s) with high centrality scores while red represent selected key player(s) for the purpose of optimally achieving certain goals corresponding to each of the four centrality measures. Green represent node(s) with high centrality scores while red represent selected key player(s) for the purpose of optimally achieving certain goals corresponding to each of the four measures.

Measure	**Description**	**Key player**[12]	**Definition**	**Theory**
Closeness			Measures a node‟s capability to quickly reach other nodes (Gil & Schmidt 1996)	Identifies individuals who would diffuse information quickly to many others (Beauchamp 1965, Valente & Davis 1999)
Betweenness			Measures a node‟s brokerage power in a network (Butt 2008)	Identifies individuals who would broker information or initiatives between disconnected groups (Stephenson & Zelen 1989)
Degree			Measures a node‟s direct connectedness with other nodes in a network (Freeman 1978)	Identifies individuals who would rapidly diffuse complex knowledge that target behavior change (Valente et al 2006)
Eigenvector			Measures the extent to which a node is connected to important others (Bonacich 1972)	Identifies individuals who would facilitate widespread diffusion of information or initiatives for behavior change in the long term (Butts 2008)

Degree centrality: This metric measures the number of direct ties a node has, and has been positively related to trust (Freeman 1978, Tsai & Ghoshal 1998), influence (Valente et al 2008), and the spread of complex contagions in social networks (Centola & Macy 2007). Complex contagions refer to information or behaviors that a node has to be exposed to through multiple contacts before it internalizes the information and/or adopts the behavior (Granovetter 1978, Karsai et al 2014). This is unlike the spreading of relatively simple information, which can transfer from one node to another through only one connection (Hill et al 2010, Wejnert 2002). In the context of social-ecological systems, high degree centrality can identify highly influential nodes with many direct contacts, and is therefore useful in identifying people who can quickly facilitate the spread of complex conservation initiatives or complex knowledge that require multiple direct contacts and persistence for adoption to occur (An & Liu 2016, Centola & Macy 2007, Granovetter 1973). Indeed, this argument is largely supported by a number of theories. Firstly, under the assumption of transitivity and triadic closure, several studies theorizes that two individuals connected to the same person with a high degree centrality are likely to be in contact themselves (Kossinets & Watts 2006, Lou et al 2013, Rapoport 1953).

Because of the strong overlaps in connections due to socio-structural bias expected in social networks (Rapoport 1953), individuals with high degree centrality are more likely to influence complex contagion cascades. Secondly, under the theory of social influence, nodes with high degree centrality are generally thought to be more influential because they tend to use more impersonal and more technically accurate sources of information (Katz 1957, Rogers & Cartano 1962), tend to be more cosmopolitan in their communication behaviour and social relationships (Katz 1957). For degree centrality, I focused on multiple direct contacts, influence, and triadic closure arguments for the transfer of complex knowledge and initiatives, however, further iterations of this framework can also include tie strength to more precisely capture complex contagions. Degree centrality is defined as follows

$$D_i = \sum_j w_{ij} + \sum_j w_{ji}$$

where w_{ij} represents the tie status from node i to node j. Thus the first term indicates the outgoing connections from node i (i.e., outdegree) and the second term the incoming connections to node i (i.e., indegree) (Butts 2008, Freeman 1979).

Eigenvector centrality: This measure builds on the degree centrality by measuring the extent to which actors are connected to others who are themselves well connected, thus affording them with a globally central position in a network (Bonacich 1972, Butts 2008). By the nature of this type of measure, which captures individuals‘ connections, but also connections of their connections, individuals with high eigenvector centrality tend to have a more global reach, and can therefore facilitate widespread diffusion of conservation behaviours. Because of the indirect connections involved, diffusion through these individuals is expected to occur over a longer time period because they would first need to influence those that are most directly connected to before these intermediaries influence others (Bonacich 1972, Butts 2008). Theoretically, spreading conservation actions through indirect contacts often favours simple processes as opposed to complex contagions because complex interventions demand a higher threshold of influence (Granovetter 1978, Karsai et al 2014). However, due to the existence of direct connections (see arguments on degree centrality above regarding direct connections), these individuals are also capable of spreading complex contagions. In a social-ecological context, eigenvector centrality can therefore be useful for identifying people who can facilitate widespread diffusion of conservation information, or widespread adoption of more complex conservation behaviors over a longer time period through their direct and indirect connections. The eigenvector centrality is calculated as

$$E_i = \frac{i}{\lambda}\sum_j w_{ij} E_j$$

In matrix notations, this is equivalent to $\lambda E = WE$, where W represents the adjacency matrix and λ the largest eigenvalue of the above equation ((Bonacich 1972, Butts 2008).

Though the metrics described above can be incredibly useful for identifying central actors in a network for different purposes (Borgatti & Everett 2006), they were not designed to select a ‗set' of individuals that, as an ensemble, would be optimally central to facilitate diffusion and/or adoption of new behaviours (Everett & Borgatti 1999). For example, if networks are disconnected or consist of less densely connected components (i.e., groups of actors that are not connected to each other by any tie), there is a high likelihood of missing individuals to facilitate diffusion in all components (i.e., groups) if one was to simply select the top *x* number of individuals with the highest centrality score (Borgatti 2006). There is also the issue of redundancy in connections. For example, degree centrality highlights individuals with the highest number of ties, yet high-degree nodes tend to connect to other high-degree nodes, and all nodes in social networks are known to preferentially form ties with those that already have a high number of ties (a process called ‗preferential attachment') (Newman 2001). Thus, high degree nodes are often connected to many of the same people – i.e., there is likely redundancy in their connections (Borgatti 2006). To address these shortcomings, an optimal criterion has been proposed to identify sets of key individuals at a group level termed the *keyplayer* algorithm[13] (An & Liu 2016, Borgatti 2006). This algorithm incorporates

[13] Keyplayer algorithm is a tool for computing individual centrality scores and optimally identifies individual key players in social networks. This algorithm also computes group centrality scores and can identify the most central group of players in a network. Selected key nodes in social networks are based on established centrality

information on centrality measures of interest, but optimally identifies key individuals depending on what they are needed for, while also redressing the computational issues and assumptions associated with each centrality measure (Borgatti 2005, Borgatti 2006, Borgatti & Everett 2006).

In order to find nodes that can reach as many remaining nodes as possible via direct links or perhaps short paths, Everett & Borgatti (1999) proposes a generic solution to the key problem. The basic idea is to treat a group of nodes as a large pseudo-node. Although several criteria are provided in An & Liu 2006, for the purpose of this analysis, I relied on the minimum and maximum criterion. According to the minimum criterion, the tie status between a group *G* and an outside node *j* is measured as the minimum of the (nonzero) edges between nodes in the group and the outside node.

$$E_{Gj} = \min_{g \in G} E_{gj}$$

This criterion ensures that there is a shortest path between the group and the outside node. It is useful for calculating geodistance related measures (An & Liu 2006). Accordingly, I used this criterion to calculate the group level measures of geodistance, i.e., closeness and betweenness centrality (An & Liu 2006).

Unlike the minimum criterion, maximum criterion measures the tie status between a group *G* and an outside node *j* as the maximum of the (nonzero) edges between nodes in the group and the outside node.

$$E_{Gj} = \max_{g \in G} E_{gj}$$

measures depending on the purpose the key players are intended for and the specific context under investigation (An & Liu 2016, Borgatti 2006).

This criterion is useful for measuring the maximal strength of the connections between the group and the outside node. By default, maximum criterion is used to compute the group level degree and eigenvector centrality. Table 8 demonstrates graphically how employing the key algorithm builds on centrality metrics but minimizes redundancy (e.g., eigenvector, Table 8) and accounts for separated components (e.g., degree, Table 8) in selecting an optimal set of two key players.

Methods

Data description

This research was conducted in all six fishing villages along the Kenyan coast (Fig. 4). This analysis is based on 238 respondents sampled during baseline surveys. In order to compare the types of individuals I identified as key for facilitating conservation diffusion (i.e., key players) with the individuals that are currently selected for engagement by conservation organizations and resource management agencies (i.e., current players), I also surveyed key informants from three government institutions and four non-governmental organizations involved in the management and conservation of marine resources in Kenya in June 2016. Key informants were presented with a list of stakeholder groups (i.e., BMU leaders, experienced fishers, highly educated fishers, vessel owners, wealthy fishers, government representatives, and non-governmental organization representatives). The stakeholder groups presented here represent key resource users that typically dominate rural fisheries settings. Using the four distinct conservation objectives, each key informant was specifically asked to indicate the stakeholders they engage with (from the list provided) when trying to achieve each diffusion-related conservation objective analysed here.

Analysis

Relational matrices based on reported fishing and information sharing ties were created and plotted in Visone (Baur et al 2001) for each site by an algorithm that uses iterative fitting on a force-directed layout (Fig. 6). I employed a weighted approach (see chapter 2) taking both the number of ties and tie weights into consideration in order to compute the four node centrality scores described in the introduction (Newman 2004).

To identify key players for each conservation objective, I calculated the four centrality scores (closeness, betweenness, degree, and eigenvector) and then applied the key player algorithm to select 10 sets of individuals for each metric following (Borgatti 2006) using the R package ‗*keyplayer*‘ for locating key players in social networks (An & Liu 2016). For closeness centrality, I calculated the harmonic measure rather than the traditional measure because my networks were disconnected (see Fig. 6; Rochat 2009). All centrality metrics were computed on undirected ties. I selected ten key players because it represented at least 20% of the sample in each site, thus representing the ‗critical mass‘ necessary for diffusion and/or adoption rates to become self-sustaining according to the diffusion of innovations theory (Rogers 2010, Valente 1996a). I quantified all overlaps between key players in each site to better understand the relationship between network structure and key players identified for achieving different diffusion-related conservation objectives.

To examine which socioeconomic characteristics most strongly predict whether an individual is likely to be an effective injection point for conservation diffusion (i.e., a key player), I ran four binary logistic regression models: one on key players selected for each of the four types of conservation objectives (where key player = 1, 0 otherwise). I included five important socioeconomic attributes as predictors: formal leadership, fishing experience, education, possession of productive fishing assets (‗productive assets‘), and material style of life (MSL) (Cinner et al 2009a) (chapter 2). As mentioned previously, formal leaders are individuals who are elected as leaders of the Beach Management Unit (BMU) responsible for community-based coastal and marine management in my study sites. In social settings, formal leaders can shape and determine the societal view of a given community (Valente 1996a).

Table 9. Socioeconomic attributes of all respondents from the six fishing villages (N = 238). Formal leaders are fishers elected as leaders of Beach Management Units (BMU), fishing experience is the number of active years spent fishing, education equals the highest grade completed, productive assets capture whether a fisher owns a fishing vessel, material style of life is a score computed from a number of household items as stand-alone attributes for indicators of wealth. Percentage for the population is relative to N, and the percentages for the villages are relative to *n* (sample size per fishing village).

	Formal leadership n(relative %)	Fishing experience (mean±SD)	Education (mean±SD)	Productive assets n(relative %)	Material style of life (mean±SD)
Population (N)	38(16%)	19.1 ± 13.9	4.7 ± 3.7	121(50.9%)	-0.1 ± 1.0
Village_A	0(0%)	13.5 ± 9.6	7.0 ± 3.1	17(14.1%)	0.9 ± 1.5
Village_B	9(23.7%)	15.9 ± 11.7	5.4 ± 2.8	16(13.3%)	0.2 ± 1.3
Village_C	6(15.8%)	18.7 ± 13.5	5.3 ± 3.7	26(21.5%)	-0.1 ± 0.9
Village_D	4(10.6%)	24.7 ± 14.8	3.6 ± 3.6	19(15.8%)	-0.4 ± 0.4
Village_E	8(21.1%)	22.5 ± 16.6	3.8 ± 4.3	31(25.7%)	-0.2 ± 0.5
Village_F	11(29%)	19.2 ± 13.7	3.0 ± 3.3	12(10%)	-0.4 ± 0.7

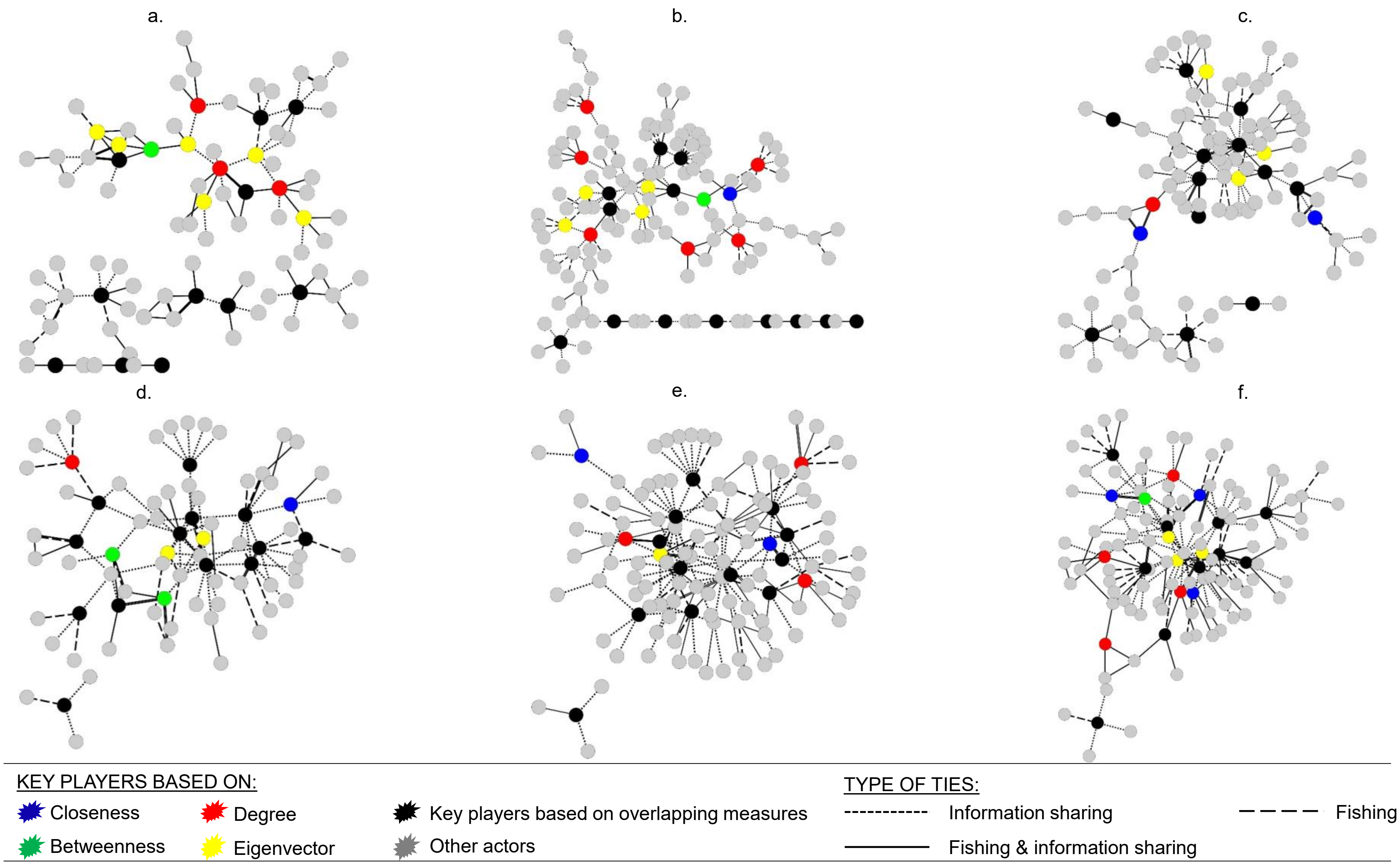

a.
b.
c.
d.
e.
f.
KEY PLAYERS BASED ON:
Closeness
Degree
Key players based on overlapping measures
Betweenness
Eigenvector
Other actors
TYPE OF TIES:
Information sharing
Fishing
Fishing & information sharing

Figure 6. Social network configuration of trap fishers in six Kenyan fishing villages (a, b, c, d, e, f; see Fig. 4). Nodes (representing actors) with the shortest path lengths were placed closest to each other in figurative two-dimensional drawings produced by an algorithm that uses iterative fitting on a force-directed layout (see Table A5 for network description). Nodes are colour coded by their identification as key players based on the four centrality metrics analysed.

They are therefore often considered opinion leaders in the conservation literature (Valente 1996a) and are typically selected by organizations for engagement in conservation and resource management. Fishing experience is defined as the number of years spent actively in fishing, which can determine whether or not one‘s opinion is respected by peers in a fishing community (McClanahan et al 2012). Education, defined as the maximum grade completed in formal education, can be an indicator of social status in a community in developing countries (Cinner et al 2009a). Possession of productive fishing assets refers to whether or not one owns a fishing boat. Material style of life (MSL) is a measure of wealth on the basis of household possessions and structure (Chapter 2). Possession of productive assets and MSL are both indicators of wealth and are often associated with social status in a community (Pollnac & Crawford 2000).

Descriptive statistics for all socioeconomic attributes are reported in Table 9. An examination of variance inflation factors indicated there was no sign of multicollinearity among these socioeconomic variables (Fox & Weisberg 2011). Site was included in my models as a random factor to account for potential differences across sites. To account for issues related to non-independence of the network data, I employed a bootstrapping procedure with 1000 random samples using replacement from the full sample to estimate robust standard errors and a 0.95 confidence interval following Barnes et al (2017). I used a 10% ($p = 0.1$) as significance indicator. All model analyses were done in R version 3.3.0 (R Development Core Team 2016).

Results

Network function and key stakeholders

848 ties used for either fishing, information sharing, or both were reported among the 238 respondents, corresponding to a mean of 2.8 ties per person. All networks were highly centralized with low levels of density and clustering, though there was some variation across sites (Fig. 6). There was some overlap (29.7%, Table A6) between key players selected (e.g., sometimes the same person was selected by the algorithm for closeness and degree centrality), though the majority of these overlaps were between two metrics only (only one person was selected as a key player for all centrality measures) and all of them varied depending on the structural characteristics of the network. For example, where there was a high number of small components that had no connection to the largest group, and I had greater overlap between key players selected based on the range of centrality scores because of multiple transitive closures, which is the tendency among two nodes to be connected if they share a mutual neighbour (Rapoport 1953).

Presence of isolates ordinarily reduce the average diameter and path length, translating into low clustering coefficients in social networks (Rapoport 1953). Clustering however appeared important for determining the level of overlaps, e.g., village E had the lowest level of clustering (clustering coefficient = 0.032) and the greatest overlap between eigenvector centrality and the other metrics, while village A had a relatively higher rate of clustering (0.081) and did not exhibit similar overlaps (see Table A5; Table A6 for a full summary of network characteristics and overlaps between key players selected for each village).

My results demonstrate that socioeconomic attributes play an important role in defining key stakeholders well placed to facilitate conservation diffusion in social-ecological systems (Fig. 5). However, depending on the conservation objective, different attributes are more or less important. For example, when rapid and efficient diffusion of conservation information is needed, which relates to the theoretical foundation of the closeness centrality measure, formal leadership ($\beta = 1.67$, $p < 0.05$) and productive assets ($\beta = 1.52$, $p<0.05$) are important for selecting key players (Fig. 7, Table A7). When brokerage of conservation actions between disconnected groups is required, which theoretically relates to the foundation of the betweenness centrality measure, my results suggest that formal leadership ($\beta = 1.96$, $p < 0.05$) is important. When the goal is to spread complex knowledge or influence behaviour change in a relatively short time scale, which theoretically relates to the degree centrality measure, formal leadership ($\beta = 1.53$, $p < 0.1$) and MSL ($\beta = 1.21$, $p < 0.1$) are both important for selecting key players. Finally, education ($\beta = 1.09$, $p < 0.05$), productive assets ($\beta = 1.76$, $p < 0.05$), and MSL ($\beta = -1.22$, $p < 0.1$) are all important for selecting key players when widespread diffusion of conservation information or long-term complex conservation initiatives are needed, which relates to the theoretical foundation of the eigenvector centrality measure.

Shown in Table 10, my findings suggest that diverging from the current strategies used to identify key players to achieve conservation diffusion goals could produce more effective results. For instance, I found that conservation practitioners have strong appeal for formal leaders and experienced fishers as key persons needed to spearhead the majority of the conservation objectives I investigated. Yet my results suggest that experienced fishers are not likely to be ideally placed to facilitate conservation diffusion. On the other hand, while community leadership is important, wealth, productive assets such as ownership of fishing vessels and levels of education are also key to identifying individuals to help facilitate conservation interventions, though the importance of each attribute varies depending on the conservation objective at hand (Table 10).

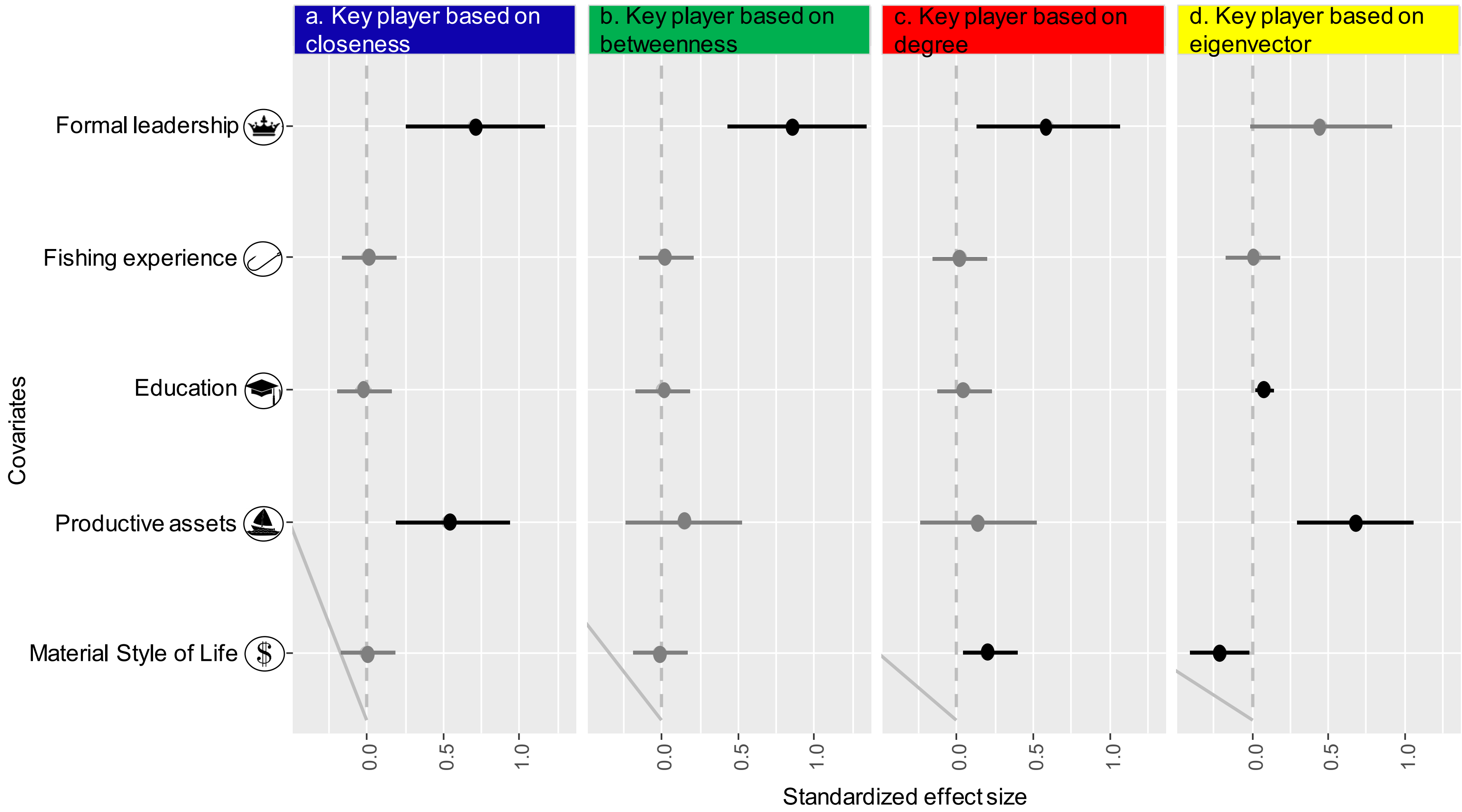
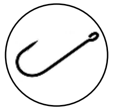
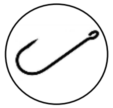
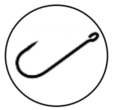


Figure 7. Estimated effect size (± 95% confidence intervals) of socioeconomic attributes associated with key players for conservation diffusion based on four different centrality metrics (a-d) using binary logistic regression models (n = 238).

Table 10. Alignment and divergence in identifying key stakeholders ideally placed to facilitate conservation diffusion. Four conservation diffusion goals are presented followed by the corresponding network metric that can help identify key players to achieve them. Socioeconomic attributes of „current players‟ selected to participate to achieve each conservation goal are then compared to the socioeconomic attributes of „key players‟, highlighting potential misalignment of effort and missed opportunities.

Conservation diffusion goal	**Relevant centrality metric**	**Current players**		
			Key players	
		Potential misalignment of effort	Correspondence	Potential missed opportunities
Rapid diffusion of conservation information	Closeness			
Diffusion between disconnected groups, (information or initiatives)	Betweenness			
Rapid diffusion of complex knowledge or initiatives	Degree			
Widespread diffusion of information or complex initiatives in the long term	Eigenvector			  

Socioeconomic factors:  Formal leadership  Fishing experience  Education  Productive assets  Material style of life

Discussion

Overall, I show that formal leaders can play a key role in facilitating a number of diffusion-related conservation goals. However, other types of stakeholders may be equally or even more important to involve when practitioners or resource management seek to spread information throughout a community and/or induce behaviour changes among a population (see Table 10). What this effectively means is that implementation of conservation goals is highly context-specific and cannot be generalized. Indeed, the inclusion and/or exclusion of certain stakeholders can and should be tailored to the specific conservation goal at hand. I discuss the theoretical and practical implications of these results in the following paragraphs before outlining my suggestions for future research.

Firstly, my findings largely reinforce the critical role that formal leaders can play in conservation initiatives. In many developing countries, resource managers and conservation practitioners are highly dependent on formal community leaders when engaging in conservation initiatives at the local level (Bodin & Crona 2008, Cohen et al 2012, Nunan 2006). In Kenya for example, fishing behaviour displays evidence of territoriality among groups, and management of marine natural resources is primarily coordinated through BMUs (Cinner et al 2009c, Oluoch & Obura 2008). These decentralized community-based management organizations allow multi-stakeholder participation in natural resource management (NRM) (Oluoch & Obura 2008) and as such, involving formal BMU leaders in conservation initiatives has been the norm among conservation practitioners and resource management agencies. However, it is improbable for a single stakeholder to effectively facilitate diffusion and adoption of all types of innovations. This scenario is due to the inherent heterophilous gap between the high level experts (managers) and the local resource users (local communities) (Arias 2015). In many cases, this gap leads to role conflicts, communication problems, social marginality (where a change agent becomes heterophilous in relation to both the local communities and managers), and information overload (where an individual is overburdened with excessive communication inputs that cannot be processed and utilized leading to breakdown) (Pratto 1999, Rogers 2010, Whelan & Teigland 2013).

In line with my results, existing research calls into question the effectiveness of relying heavily on formal leaders for achieving all types of conservation objectives. For example, Barnes-Mauthe et al (2015) showed that formal leadership was not significantly related to being centrally placed in a social community of commercial tuna fishers, which they argue was responsible, at least in part, for the failure of a conservation tool aimed to reduce sea turtle bycatch (which was introduced only to formal leaders) to diffuse and be adopted throughout the community. Others have argued that formal leaders may be more able to facilitate coordination and the flow of conservation information rather than influence widespread adoption of conservation actions per se (Balkundi & Kilduff 2006, Bodin & Crona 2008, Dearing et al 2006, Edmondson 2003). This is partially supported by my results showing that formal leadership is not important for predicting key players ideally placed to facilitate widespread diffusion (Fig. 7). However, formal leadership was important for predicting key players for all of the other conservation objectives studied, and was in fact the only attribute that significantly predicted key players to act as brokers between potentially disconnected communities. Yet this brokerage power may only apply to less complex conservation actions or innovations with minimal social and technical chasms between social groups which require coordination as opposed to influence to spread (Duffy 2010, Pajaro et al 2010). Thus, when the goal involves complex conservation actions spreading through fragmented communities, additional centrality measures such as degree and/or eigenvector should be included as a complement to betweenness centrality for identifying key players.

In combination with existing work, my results also suggest that the importance of formal leadership to conservation diffusion depends on the social network structure underpinning stakeholder organization. For example, the work by Barnes-Mauthe et al (2015) showed that formal leadership was not critical for predicting a large range of centrality metrics in a highly decentralized society of fishers where social network structure was largely defined by ethnicity. In contrast, my study sites were all in Kenya, a highly centralized and hierarchical society which is reflected in fisher's social networks. Over 87% of the respondents in all villages belong to one ethnicity with majority (>91%) indicating not to have lived away from home (see Table 11 for more details on ethnicity and migration behaviour for fishing villages surveyed). These societal differences may partly explain my contrasting results.

Depending on the social structure and the conservation objective at hand, my results show that involving other types of individuals in addition to, or instead of formal leaders to facilitate diffusion is key for certain conservation objectives. For example, though institutional responses showed a wide appeal to select formal leaders and experienced fishers to facilitate rapid spread of less complex conservation actions, my results show that experience is not significantly related to identifying key players for this objective (Table 10). Moreover, failure to involve people with productive assets (such as vessel owners in fishing communities), which was at least as important as formal leadership for identifying key players for this objective, can be a potential barrier for successful implementation. Productive assets in addition to MSL and education are also important for identifying critical injection points to facilitate the adoption of more complex conservation actions for behavior change, both in the long and short term. Existing research by Cinner et al (2009a) and Pollnac & Crawford (2000) has similarly suggested that these factors can be indicators of social status in communities, and can therefore be important for influencing decision making processes (e.g., adoption of new technologies). In the present study, wealthier fishers tended to have high degree centrality scores, suggesting they would have more opportunities to directly influence others when a new conservation action is recommended for behaviour change. Similarly, people with productive assets (i.e., vessel owners) and those who were highly educated had more ties with others who were themselves well-connected throughout the network. This implies that while original knowledge of a conservation practise can be gained from official sources, i.e., from formal leaders, targeting a broader combination of socially influential stakeholder groups may be more effective to galvanize the process of reaching a critical mass when initiating more complex conservation actions – such as those expected to spread widely in the long-term or those that seek to change behaviour in the short term (Conley & Moote 2003, Valente & Davis 1999). Perhaps more importantly, excluding these stakeholders may have inhibiting effects on adoption and diffusion of more complex conservation innovations (Bongaarts 1994, Nabseth & Ray 1974). This sort of conservation diffusion strategy has the added benefit of being somewhat less vulnerable to fragmentation even if the role of one type of stakeholder is lost or ineffective (Borgatti & Foster 2003).

My results regarding wealth and productive assets bring to light ethical questions regarding elite capture. Conservation initiatives are often participatory projects aimed to improve ecological health and the livelihoods of rural people who depend on natural resources (Mertens et al 2005, Platteau 2004, Saito-Jensen et al 2010). However, these projects have often had limited success in targeting the poorest due to situations of elite capture (Agarwal 1997, Mansuri & Rao 2004, Platteau 2004, Springate-Baginski & Blaikie 2013), where the more privileged members of communities dominate decision making processes and, at the expense of other groups, improve their access to collective benefits (Ribot 2007). In the present study, I recognize and highlight the importance of MSL – a measure of wealth – in selecting key players in the conservation process. In fact, I show that elites often hold key structural positions well-placed to facilitate the spread of complex conservation actions for behaviour change. This suggests that conservation efforts even in rural communities may be particularly vulnerable to elite capture depending on existing inequality and hierarchies

(Cleaver 1999). Yet it is important to note that not all elites who have power are corrupt (Saito-Jensen et al 2010), a finding that highlights the important distinction between elite control and elite capture. For example, in investigating community driven development actions and elite capture in Indonesia, Dasgupta and Beard (2007) showed that in cases where participatory projects were controlled by elites, benefits continued to be delivered to the poor, yet where power was the most evenly distributed, resource allocation to the poor was actually restricted (Dasgupta & Beard 2007). Thus, while participatory approaches may face initial elite capture, this should not prevent us from seeing their positive long-term potential so long as these elites are willing and able to contribute their time and know-how needed to facilitate community-level projects and governance. Additionally, if elites adopt good conservation initiatives with more frequency and intensity compared to non-elites (Fung & Wright 2003), then this cause might still safeguard environmental objectives.

My results also show that non-elites should be brought on board for widespread impact of conservation initiatives to be achieved. In other words, for real impact to be achieved, managers must find ways of enabling poor fishers to adopt conservation activities. In the social-ecological context, scholars have previously noted that wealthy individuals have quick tendencies to embrace advanced fishing technologies and innovations to increase their fishing efficiency, catch rates, and direct economic gains (Brewer et al 2006, Deudero et al 1999, Kjelson & Johnson 1978, Reiss et al 2006). By the same token, poor individuals have consistently been constrained financially to adopt these technologies due to the high investment cost and risk associated with adoption. In a way, people‘s wealth status has always determined susceptibility of potential adopters to new ideas and practices (Feder et al 1985). However, since the majority of the fishers in rural communities are poor, managers may resort to other strategies for getting to the critical mass, such as offering incentives or shaping adoption inevitability perceptions (i.e., by implying that the innovation is very desirable and adoption is inevitable) to early adopters to enhance adoption (Rogers 2010). Still, it is important for participatory approaches to be designed in a way to either avoid or minimize the risk of elite capture with a view of promoting equity participation (Mertens et al 2005), particularly in communities where it is unclear whether avenues are available to local residents to redress elite capture and other problems common to development and conservation in social-ecological systems. This precaution is particularly critical in rural coastal communities dominated by marginalized groups (non-elites) who generally depend more than others on natural resources.

Conclusion

Here I highlighted a mismatch between ideal strategies and current strategies applied to identify stakeholders to facilitate diffusion-related conservation objectives. By providing a specific criteria to guide the selection of relevant stakeholders to spearhead four specific conservation goals, I not only offer practical solutions to better identify critical injection points to achieve intended conservation objectives, but also help to mitigate the problem of stakeholder identification in ways that avoid blueprint approaches or panacea (Ostrom 2007). By showing how other key players have been overlooked in the current conservation strategy, my findings indicate that continued failures to achieve sustainability in coastal social-ecological systems (Botsford et al 1997) may in part be attributed to the absence of specific guidelines to assist in identifying relevant stakeholder representation in conservation diffusion processes.

Chapter 5: Evaluating outcomes of conservation diffusion using multidimensional indicators of wellbeing

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Synopsis

Many conservation interventions are hypothesised to be beneficial for both the environment and people‘s wellbeing (i.e. a win-win), but this has rarely been rigorously tested. Here, I examine the effects of adoption or non-adoption of a conservation intervention on three dimensions of people‘s wellbeing (material, relational, subjective) over time. I collected panel data from fishers (n = 250) in both control (without the intervention) and experimental villages (with the intervention) encompassing three observations over two years. Across multiple domains of wellbeing, I find no evidence that adoption did any harm to the local populations affected by the intervention. Indeed, I show modest improvements in material and subjective livelihood wellbeing for adopters relative to controls over time. The variations I find in wellbeing experiences (in terms of magnitude of change) among adopters, non-adopters, and controls across the different domains over time affirms the dynamic and social nature of wellbeing. Findings provide a more holistic picture of the consequences of conservation diffusion processes on human associated communities.

Introduction

Implementation of new ideas and practises can have both positive and negative outcomes on people (Rogers 2010). Understanding the consequences of transformative conservation ideas and practises on people is therefore critical. For example, demonstrating positive outcomes of conservation on people could improve cooperation and support for collective action among local people (Milner-Gulland et al 2014). Conversely, implementation of conservation would be somewhat difficult if negative impacts on people are associated with interventions (de Lange et al 2016). Indeed, assessing impacts on people from a biodiversity conservation intervention can help identify winners and losers in the social-ecological system (Leisher et al 2013).

To date, evaluations of the impacts of conservation interventions on people are rarer than those focused on the environment (de Lange et al 2016, Milner-Gulland et al 2014, Woodhouse et al 2015). The limited evaluations exploring the effects of conservation on people‘s wellbeing tend to use monetary indicators or material measures of poverty (Charles et al 2015, Cochrane 2000) - examinations that are biased towards economic dimension of people‘s wellbeing and are largely premised on material deprivation and a deficit centred perspective (Coulthard 2012, Weeratunge et al 2014). Meanwhile, there is increasing consensus in international policy circles that wellbeing is multidimensional (Leisher et al 2013). Recent conceptualisations of wellbeing have indeed moved toward a three dimensional framework comprised of material, relational, and subjective dimensions (Abunge et al 2013, Gough & McGregor 2007). Material wellbeing captures objective material resources such as income, assets, livelihoods, employment, and the natural environment that a person can draw upon to meet their needs (Coulthard 2012, Gough & McGregor 2007). Relational wellbeing entails what people do through social relationships that facilitates/or hinders the pursuit of good life (Narayan-Parker 2000). These connections may include forms of collective action, relationships of care and love, social institutions, or cultural rules and norms (Coulthard 2012, Gough & McGregor 2007). Subjective wellbeing encompasses how a person thinks and feels about their life and what they have and do with what they have (Coulthard 2012, White 2010). Together, these concepts can be used to positively or negatively evaluate the extent to which actions or decisions affect people (Breslow et al 2016).

Calls for a more holistic approach to studying wellbeing in the conservation discourse have been accompanied by recent methodological guidelines (Woodhouse et al 2015), but empirical studies are still rare. Indeed, no study to date has compared how multi-dimensional aspects of wellbeing between adopters and non-adopters of conservation initiatives change over time. Here, I ask ―how does adoption of a conservation intervention influence material, relational, and subjective wellbeing?” To provide a more robust and comprehensive evaluation of outcomes, this analysis draws on a before-after-control-intervention (BACI) design. The design combines controls (villages where the escape slot trap was not introduced), intervention villages (where the escape slot trap was introduced), and baselines. Having controls allowed changes in wellbeing conditions to be explicitly attributed to intervention studied. Given that wellbeing outcomes can change through the course of an intervention (McGregor 2007), this study adopted a longitudinal approach that include baselines to monitor trajectories on change over time.

I integrate both objective and subjective measures of wellbeing, to better understand how a conservation intervention affects both what people have (objective measures) and how they feel about what they have (subjective measures). By combining objective and subjective evaluations of wellbeing, I emphasize the holistic, dynamic and social nature of wellbeing (Camfield et al 2009b). This brings together a novel configuration of independent and interdependent domains, counterbalancing the current trends in environmental policy that privilege objective material measures of wellbeing (Woodhouse et al 2015). This approach further reinforce the value of subjective feelings, perceptions, and social dimensions of people's lives that are often underplayed when evaluating conservation (McGregor & Sumner 2010). My evaluation further integrates the key aspects of casual and associated counterfactual analysis both theoretically and methodologically in order to ensure any changes in the outcome can be attributed to the intervention (see chapter 2).

Methods

Study design

This research was conducted in all six study villages (i.e. both experimental and control sites). I employed a before-after-control-intervention (BACI) design to assess whether the escape slot traps affected wellbeing (Smith 2014). This method compares changes in outcomes (here, wellbeing indicators) between adopters of the escape slot trap relative to non-adopters and control villages (where the escape slot trap was not introduced) over time. The BACI design therefore accounts for bias due to: (1) initial differences in wellbeing between adopters, non-adopters, and controls; and (2) changes in wellbeing that are a result of broader-scale trends (Ferraro & Hanauer 2014). Controls sites are of special relevance to evaluation research because what matters to people in their assessment of their quality of life can be changed by the intervention itself (Milner-Gulland et al 2014). Controls were selected based on their similarity with the intervention sites in regards to a suite of measurable conditions such as fishing gear utilization and resource dependency. To avoid spillover effects of the project or contamination by other interventions, I selected control sites situated several kilometres way (>20km) from the intervention sites and without an ongoing conservation project. This selection criterion is consistent with the guiding principles for evaluating impacts of conservation interventions on human wellbeing and the theory of change (Woodhouse et al 2015). To ascertain whether changes in wellbeing are immediately or eventually reflected in conservation outcomes I collected data between October 2015 and January 2018. In this time, I conducted a baseline survey before the conservation practice was rolled out, followed by two follow-up surveys one and two years later after the launch of the project. The same questions were asked of the same participants in experiment and control sites, in all three time periods. Fishers that adopted but later abandoned using the escape slot trap (dis-adopters) were still considered adopters because they had used the intervention.

Operationalising wellbeing

Material wellbeing: I measured one component of material wellbeing, material assets, represented by material style of life (MSL; Table 11). MSL is an indicator of wealth based on a locally grounded assessment of a wide range of household possessions and structure (Cinner et al 2009a). MSL captures ones quality of the living environment and can be a robust measure of economic and material wealth (Woodhouse et al 2015). I use MSL rather than income due to its preponderance in studies and importance as comprehensive indicator of material resources. In chapters 3 and 4, I used a factor analysis to create a wealth metric from the first axis of a principal component analysis (PCA). However, for this chapter I had to modify this slightly. Because each respondent had three observations in time, each with potentially different material assets, I could not use the PCA from earlier chapters. Instead, I used factor loadings created from the baseline state to weight each of the MSL items, which allowed me to create wealth scores that were directly comparable between the three sampling periods. To assess the reliability of scores across the different sampling periods, I used the Cronbach's alpha technique (Tavakol & Dennick 2011). Cronbach's alpha determines the average correlation or internal consistency among factors extracted from multipoint and/or dichotomous formatted scales (Santos 1999). A value of 0.89 indicate that the use of factor loadings was reliable at the 5% level of significance and therefore the MSL scores are suitable for further analysis (Nunnally 1978).

Relational wellbeing: Relational wellbeing was operationalized using a measure that captures relational balance of social relationships as developed in the network theory (Buunk & Schaufeli 1999, Sadilek et al 2018, Tóth et al 2018). Relational balance is grounded on the notion of giving and receiving which allows relational benefits such as social capital to be shared among members of a social system through social exchange (Leana III & Van Buren 1999). A good social relational balance is a critical component of social relationships because it underpins how peoples relationships can be evaluated especially where social connections constitutes critical pathways through which people access other human needs and benefits in the society (Sadilek et al 2018). Indeed, a good relational balance can determine the nature of individuals' social embeddedness, whereas relational imbalance can be a reflection of relational tensions as a result of behaviour change, e.g., adoption of high-risk conservation intervention such as the escape slot trap (Tóth et al 2018). Here, I looked at reciprocity (i.e., number of reciprocated ties) based on fishing and information sharing ties. In the current context, these two relationships (fishing and information exchange) are critical for fishers in their pursuit of wellbeing because majority of households depend primarily on fishing to support their livelihoods.

Subjective wellbeing: Subjective wellbeing was operationalized using three indicators that captured individuals' perceptions of different components of their lives. In developing these indicators, I drew on a framework developed from wellbeing assessments on coastal fishing villages in Kenya that identifies the three most important domains for their quality of life (Abunge et al 2013). For the items covered in Abunge et al (2013), participants indicated how satisfied they were with their food and income situation (livelihoods wellbeing, i.e., livWB), social relationships with other members of the community (cohesion wellbeing, i.e., cohWB), and their job (work wellbeing, i.e., worWB) (Table A8).

Table 2. Multidimensional framework used in the assessment of wellbeing outcomes[a]. Qualitative, quantitative indicators and data sources for the multiple domains of wellbeing. The indicator of relational of wellbeing i.e., reciprocity (number of reciprocated ties) is based on fishing and information sharing ties. The two relationships (fishing and information exchange) are deemed critical for fishers in their pursuit of wellbeing because majority of households depend primarily on fishing to support their livelihoods.

Wellbeing dimension	Indicator type	Outcome	Indicator	Data type
Material What you have	⇨ Basic needs satisfaction	Wealth	1. **Material style of life** (i.e., possessions of key assets & type of household structure)	Interval
Relational Your social connections	⇨ Social relationships	Relational balance	2. **Reciprocity** (i.e., number of reciprocated ties)	Interval
Subjective How you feel about what you have and your social relationships	⇨ Experienced quality of life	Perceptions about food & income	3. Quantified satisfaction levels regarding food & income **(livWB)**	Ordinal; Likert scale 1-5
		Perceptions about social cohesion	4. Quantified satisfaction levels regarding relationship with community members **(cohWB)**	Ordinal; Likert scale 1-5
		Perceptions about work enjoyment	5. Quantified satisfaction levels regarding work enjoyment & identity **(worWB)**	Ordinal; Likert scale 1-5

[a]Source: adapted from the guiding principles for evaluating the impacts of conservation interventions on human wellbeing Woodhouse et al (2015) and drawing on Britton & Coulthard (2013), McGregor & Sumner (2010), and the World Bank"s „Voices of the Poor" research (Narayan et al 2000). I draw on network theory of wellbeing to conseptualize relational wellbeing (Ayalon et al 2018, Borgatti et al 2018, Sadilek et al 2018, Tóth et al 2018).

These constructs not only provide a condensed assessment of quality of life (Priebe et al 1999) but are also complimentary to the objective measures. Assessment of subjective wellbeing was conducted by means of 5-point Likert scale questions with endpoints very satisfied – very unsatisfied. I triangulated my subjective measures using a categorical question that captured perceived change in wellbeing. Specifically, I asked fishers to state whether they felt a change (based on a 5-point Likert scale) in the three domains of subjective wellbeing over the time period of the study. In so doing, I was able to determine whether my subjective measures were robust.

Analysis

Firstly, I examined whether there were differences in wellbeing conditions between adopters, non-adopters, and controls at the baseline time using rank based Kruskal-Wallis H test. I then used proportional odds models to test for differences in the three dimensions of subjective wellbeing (ordered categorical data), and a general linear mixed model with a Gaussian distribution was used for material and relational wellbeing (continuous data). Because my study uses panel data with at least two observations for each respondent, all analysis on differences between adopters, non-adopters, and controls are presented as deltas (i.e. the difference between wellbeing conditions at baseline level, T_0 from conditions during the first follow-up (short term, T_1) and second follow-up (medium term, T_2). The design involved testing the effect of the categorical explanatory variable (adoption, control villages, and non-adoption) – on each of the different domains of wellbeing (the response variables) (Table 12). Adopters were set as the reference category. To improve the attribution of the effects to the intervention versus other socioeconomic conditions occurring in the community, I controlled for covariates that have been shown previously to influence wellbeing outcomes in fisheries social-ecological settings (Gurney et al 2016). These are formal leadership, fishing dependency, access to credit, occupational multiplicity, age (age of the fisher years), education (maximum grade completed in formal education), and marital status (Table 3; Table 12).

Table 3. List of variables used in the analysis. Material style of life is a score computed from a number of household items as stand-alone attributes for indicators of wealth. Reciprocity captures the number of reciprocated ties based on fishing and information sharing ties. Levels of satisfaction regarding food and income (i.e., subjective livelihood wellbeing), social relationships with other community members (i.e., subjective social cohesion), and work enjoyment and identity (i.e., subjective work wellbeing) are denoted as livWB, cohWB, worWB respectively. Non-adopters are individuals who never used the escape slot trap in villages where the intervention was introduced. Controls are individuals from villages where the escape slot trap was not introduced. Description of control variables as in Table 3.

Wellbeing dimension	**Response variables**	**Predictor variables**	**Control variables**
Material	Material style of life	Adopter	Age
Relational	Reciprocity	Non-adopter	Occupational multiplicity
Subjective	livWB	Control	Fishing dependency
	cohWB		Formal leadership
	worWB		Education
			Marital status
			Credit access

An examination of variance inflation factors indicated there was no signs of multicollinearity among these socioeconomic variables (Fox & Weisberg 2011). Summary statistics (i.e., mean, standard deviation, minimum, maximum, and percent proportions) of all control variables included in the regression frameworks are reported in Table A8. Site was included as a random factor to account for the hierarchical nature of the data (i.e. individuals nested in sites). All timescale results are presented over the short and medium terms. The relevant assumptions were tested for each of the statistical models (e.g. normality and homogeneity of variances for linear mixed models). I also ran linear models for wellbeing and compare results with the proportional odds models. No differences were noted in the results and therefore not presented. Network data were analysed using UCINET for Windows version 6 and Gephi version 0.9.2 (Bastian et al 2009, Borgatti et al 2002). All statistical analyses were conducted using R software (version 3.4.5).

Results

Baseline conditions

Of the 250 respondents, 42% adopted the escape slot trap, whereas non-adopters and controls are represented by 29.2% and 28.8% of the sample respectively (Table A8). I found no evidence that there were differences in baseline values between adopters, non-adopters, and control villages for the different domains of wellbeing, except for MSL (Table A9). This suggests that the parallel trend assumption is likely to hold, except for MSL, and thus those results in particular should be interpreted with caution.

Changes in wellbeing over time

Mean changes in wellbeing for adopters, non-adopters, and controls for each individual fisher are presented as deltas over the short and medium term (Fig. 8). Improvements in material wellbeing (MSL) for adopters were slightly higher compared to non-adopters and controls in the short term. Both adopters and non-adopters within villages where the escape slot trap was introduced showed even greater improvements in material wellbeing in the medium term relative to the magnitude of change they experienced in the short term (Fig. 8). Only a slight increase in material wellbeing was experienced by control villages in the medium term relative to the magnitude of change recorded in the short term. Changes in relational wellbeing (reciprocity) for adopters, non-adopters, and controls were relatively similar in the short term, although non-adopters appeared to have experienced a slightly higher magnitude of change. Short term gains in relational wellbeing among adopters and non-adopters were however lost in the medium term (Fig. 8).

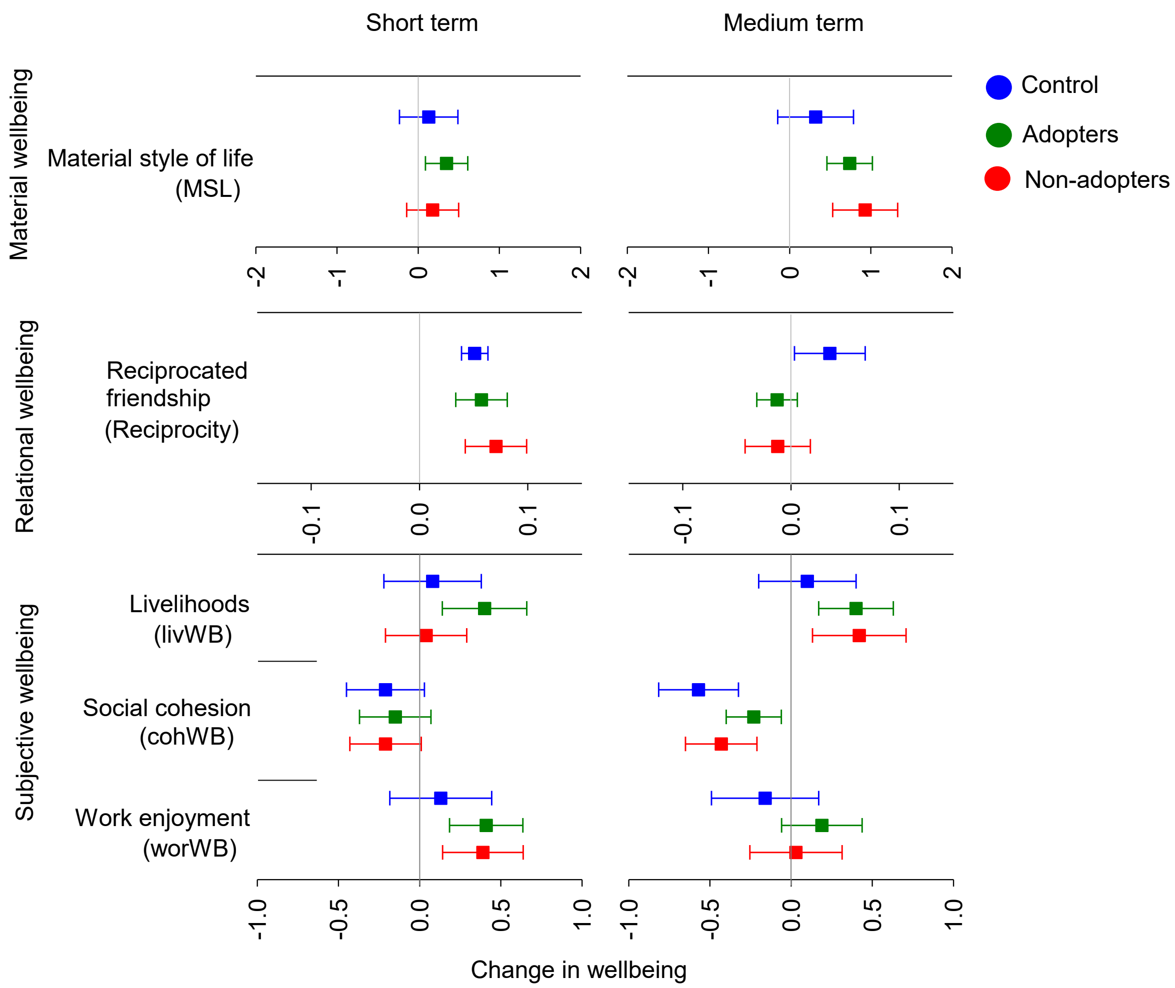

Figure 8. Mean changes wellbeing among adopters, non-adopters and controls over the short (T_1) and medium term (T_2). Mean change is relative to baseline (T_0). Domains for subjective wellbeing are as follows: how satisfied they were with their food and income situation (livelihoods wellbeing, i.e., livWB), social relationships with other members of the community (cohesion wellbeing, i.e., cohWB), and their job (work wellbeing, i.e., worWB) (Abunge et al 2013, Priebe et al 1999). The indicator of relational of wellbeing i.e., reciprocity (number of reciprocated ties) is based on fishing and information sharing ties.

Changes in relational wellbeing in control villages were maintained at the same level in either time period. Improvements in subjective livelihood wellbeing (livWB) for adopters were slightly higher compared to non-adopters and controls in the short term. The level of change in subjective livelihood wellbeing for non-adopters was greater in the medium term relative to the magnitude of change they experienced in the short term. Changes in subjective livelihood wellbeing among adopters and control villages were maintained at the same level in either time period (Fig. 8). There was consistent decline in subjective social cohesion wellbeing (cohWB) among all three groups (i.e., adopters, non-adopters, and controls) in either time period. A more detailed observation however shows that social cohesion decreased less among adopters than non-adopters and controls in either time period. Improvements in subjective work related wellbeing (worWB) for adopters and non-adopters were relatively higher compared to the control villages in the short term. Although these improvements were maintained for adopters in the medium term, short term gains in subjective work related wellbeing among non-adopters and controls were lost in the medium term (Fig. 8).

Differences in changes in wellbeing over time

The increase in adopters' material wellbeing in the medium term was greater than changes experienced within the control villages, but adopters' increases did not differ from that experienced by non-adopters' in either time period (Fig. 9). There was no significant difference on changes in relational wellbeing among adopters relative to non-adopters and controls in either time period. The increase in adopters' subjective livelihood wellbeing in the short term was greater than any changes experienced within the control villages and non-adopters within experiments where the escape slot trap was introduced. However, adopters' increases in subjective livelihood wellbeing did not differ from that experienced by non-adopters and controls in the medium term. The decrease in controls' subjective social cohesion wellbeing in the medium term was greater than changes experienced by adopters. No significant difference on changes in subjective social cohesion wellbeing was detected among adopters relative to non-adopters and controls in the short term (Fig. 9). The increase in adopters' subjective work related wellbeing among adopters over the short and medium term did not differ from that experienced by non-adopters and controls in either time period

(Fig. 9). Testing for robustness of my subjective measures of wellbeing, I show strong correlation between perceived and actual change across all three domains for the three groups sampled (Fig. A1). Socioeconomic factors that were related to changes in wellbeing dimensions include access to credit, formal leadership, education, fishing dependency and marital status (see full model results in Table A10).

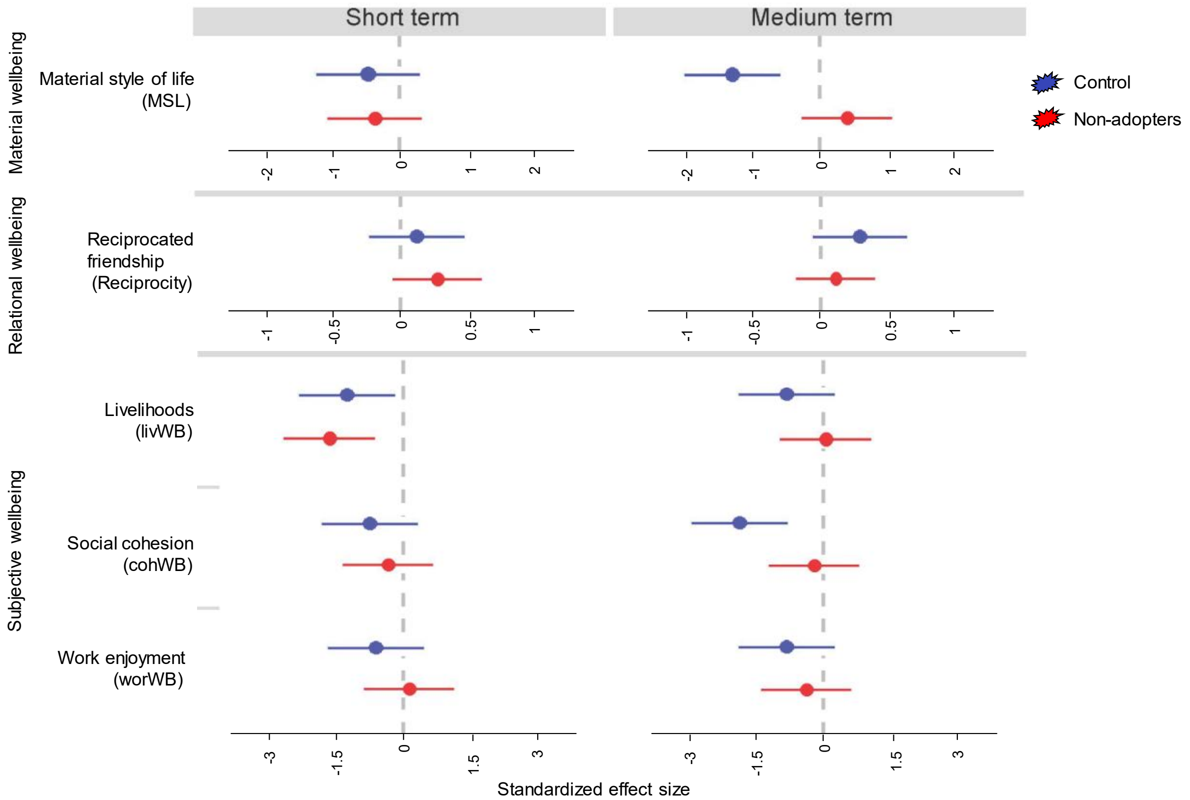

Figure 9. Difference in changes in wellbeing between adopters and controls (blue) and non-adopters (red) of escape slot traps assessed in the short and medium term. Differences in changes in wellbeing associated with the response variable were contrasted with the base category, i.e., adopters.

Discussion

The impacts of conservation on associated human communities remain a topic of contentious debate (Milner-Gulland et al 2014, Woodhouse et al 2015). Here, I emphasize the relevance of multiple domains of wellbeing, to better understand how a fisheries conservation intervention (i.e., escape slot trap) affects both what people have (objective measures) and how they feel about what they have (subjective measures) (Coulthard et al 2011). Overall, I show notable variations in the magnitude of change in wellbeing conditions experienced by adopters, non-adopters, and controls over two time period. This affirms that wellbeing is not a discrete outcome, but an ongoing dynamic process, changing through time or in the course of an intervention (Woodhouse et al 2015). Short term and medium term gains in terms of material, subjective livelihood, and work enjoyment wellbeing was higher for adopters relative to controls. Though adopters showed a decrease in relational wellbeing in the medium term, differences in the level of change between adopters, non-adopters, and controls were not significant. Aside from subjective livelihood wellbeing where the short term gains for adopters were higher than changes experienced by non-adopters, no significant differences were observed between adopters and non-adopters in all other domains of wellbeing over time. Consistent decline in subjective social cohesion wellbeing for adopters cannot be attributed to the intervention because similar trends were observed among non-adopters and controls. Taken together, these results show no evidence that the conservation intervention did any harm to people that adopted it.

This study is the first to examine how wellbeing outcomes differ among adopters and non-adopters of conservation interventions using a BACI approach. I highlight intricate and diverse links between wellbeing and conservation, some of which could be specific to the conservation intervention studied here (i.e., escape slot trap). Foremost, the variation I found in wellbeing experiences among adopters, non-adopters, and controls over time in my longitudinal analysis affirm the dynamic nature of wellbeing (Woodhouse et al 2015). These findings reflect Gurney et al (2014)'s study of the impacts of protected areas over three time periods, and highlights the importance of going beyond typical approaches of measuring outcomes over a single time period to examine out the impact of an intervention may differ at various points of time after its implementation. My analysis also shows that short term gains in some aspects of wellbeing can be lost over time. For example, adopters experienced greater changes in subjective livelihood wellbeing in the short term relative to controls and non-adopters. However, these short term improvements were narrowed between the three groups (i.e., adopters, non-adopters, and controls) in the medium term. Baseline shifts, i.e., the change back to using normal unmodified traps by dis-adopters perhaps could have contributed to the loss of short term gains in some aspects of wellbeing. These findings are mirrored in other studies that showed the loss of initial gains in terms of empowerment and wealth among beneficiaries of marine protected areas in Indonesia (Gurney et al 2014); highlighting the need for long term monitoring of conservation outcomes on affected populations.

Changes experienced by adopters and non-adopters within experiments (i.e., where the escape slot trap was introduced) across multiple domains of wellbeing were greater than those in control villages in either time period. However, changes experienced by adopters relative to non-adopters within experiments did not show much difference in either time period. This means that the presence of the intervention within experiments had an impact on people‘s wellbeing over time. Indeed, the benefits associated with the intervention were illuminated by the modest improvements in material wellbeing for both adopters and non-adopters within experiments over the medium term. In many cases, bycatch management initiatives (such as the one studied here) are often introduced to protect biodiversity (e.g., by letting small and non-target fish exit though escape slots) (Johnson 2010). It is often expected that improved ecological conditions will in turn lead to increased catches over time (McClanahan & Kosgei 2018). Subsequently, higher catches are expected to translate into positive socioeconomic outcomes e.g., improved income and livelihoods that will continue to accrue over the long term (Christie 2000). In this context, some degree of spillover of benefits perhaps explains the improvements of wellbeing for both adopters and non-adopters of escape slot traps within experiments.

There were no differences in changes experienced by adopters, non-adopters, and controls in terms of subjective work related wellbeing and relational wellbeing in either time period. This means that neither the presence of the intervention in experimental villages nor adoption of the escape slot trap was sufficient to significantly alter perceptions about fishing as well as social relationships among fishers studied. Previous research has shown that fishers have a strong attachment to fishing as an occupation even with diminishing returns (Cinner et al 2009a). Indeed, in small-scale communities where fishing supports a significant portion of the population, perceptions about fishing might be deeply entrenched into the fabric of the society. This suggests that reshaping fisher‘s opinion on any component about fishing or social connections in the community can be challenging - a key observation that need to be recognized in fisheries governance.

It is acknowledged that the presence, absence, or adoption of the conservation intervention might not explain all trends observed in this analysis. For example, I found consistent decline in subjective social cohesion wellbeing among adopters, non-adopters, and controls in either time period. These trends indicate that changes or breakdown of social cohesion should be attributed to other factors rather than presence or absence, adoption or non-adoption of the conservation intervention. Thus, despite my rigorous sampling design other socioeconomic trends that might have occurred within villages studied that could have funnelled this trend. However, the fact that social cohesion decreased less among adopters and non-adopters (within experiments) than controls in either time period may suggest that the presence, but more so adoption of the conservation intervention within experiments had a buffering effect on the consistent breakdown of social cohesion over time.

This study employed an alternative approach in assessing relational wellbeing using an indicator of relational balance as captured in the network theory. Prior to this study, evaluations on relational outcomes of conservation had favoured subjective questions that simply capture how satisfied one is with their social relationships in the wide community (Breslow et al 2016, Britton & Coulthard 2013) - as I also did here. However, relying on such general questions that are far removed from the intervention can result in attribution errors because people tend to maintain social relationships comprising hundreds of members (Warriner & Moul 1992, Woodhouse & Emiel de Lange 2016). Yet, at the heart of evaluation is the process of attributing specific effects to the intervention rather than to other intervening factors in the wider community (Woodhouse et al 2015). The value of the network approach in assessing relational wellbeing in the context of conservation was demonstrated in the findings. The buffering effect associated with the presence of escape slot traps within experiments (i.e., subjective social cohesion decreasing less among adopters and non-adopters than controls) was not reflected in the patterns of relational wellbeing (i.e., reciprocity). Instead, controls appeared to have more reciprocated ties (i.e., improved relational wellbeing) compared to adopters and non-adopters in the medium term. I cannot conclude that there was a decrease in relational wellbeing among adopters relative to non-adopters and controls because differences between the three groups were not significant. These findings can potentially challenge the traditional approach on how relational wellbeing has been conceptualized in impact evaluation research. The network property used here, (i.e., reciprocity - tendency that two people that are connected speak to each other) deemphasize on numeric properties of networks and can be applied to any evaluation design regardless of the intervention or the number of nominations made by respondent.

Conclusion

Calls for putting human communities at the centre of impact evaluation studies have suffered from lack of methodological robustness and rarely pointed to clear cut arguments about net outcomes (Beauchamp et al 2018a, Biedenweg & Gross-Camp 2018). Here, I use a set of comprehensive indicators that capture the complex and multidimensional nature of wellbeing over time (Dawson et al 2018). In so doing, I bring together a novel configuration of independent and interdependent domains, counterbalancing the current trends in environmental policy that privilege objective material measures of wellbeing (Woodhouse et al 2015). The variation I found in wellbeing experiences between adopters relative to controls and non-adopters over time affirms the importance of taking a disaggregated and longitudinal approach in future evaluation research. Given the impact of the intervention differed between dimensions of wellbeing, I contend that even if material and other objective needs for target populations are met, imposing conservation policy that fails to capture hidden non-material aspects of wellbeing could potentially be problematic. Future assessments of wellbeing in fisheries social-ecological systems should perhaps look deeper into the effect of other socioeconomic conditions such as education, opinion leadership, and dependency in fishing. These socioeconomic factors were related to changes in wellbeing experiences among fishers at different time scales. The heterogeneity in socioeconomic conditions among various social groups in social-ecological systems might result in differences in the way impact of conservation is felt on people over time.

I find no evidence that adoption of the conservation practice was detrimental to the overall wellbeing for adopters; indeed I find modest improvements in material and subjective livelihood wellbeing for adopters relative to controls over time. This study therefore provides wider legitimacy and support towards gear-based conservation strategies particularly in rural economies where acceptability of participatory conservation interventions remain a key challenge. Longer term monitoring is however strongly recommended to provide understanding of whether the material and subjective benefits will continue to accrue over time. Sustained improvements over the long term could provide a more sustainable basis for pathways out of poverty hence increasing the resilience of communities engaged in conservation. Given the difficulties in measuring outcomes, findings of this study can be used to inform environmental policies and interventions such as collaborative governance and collective action (Scott & Thomas 2017). Although my study adopts frameworks that are grounded in the theoretical strands of wellbeing, the interaction of other dimensions of human wellbeing such as human rights, capabilities, resilience, and vulnerability should be seen as a new research frontier.

Chapter 6: Ecological implications of a gear based conservation intervention

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Synopsis

An analysis of ecological implications of the escape slot trap provides evidence of whether adoption of the conservation intervention is beneficial to the environment. I employ a functional trait-based approach to determine whether escape slot remove and potentially compete with other gears for fishes with unique combinations of functional traits (diet, body size, depth, position in water column, period of activity, schooling behaviour) in a coral reef fishery. Data from 25 fish landing sites across Kenya over a seven-year period show that fish assemblages in escape slot traps carry the least functionally diverse assemblages. Nets, including gillnets and beach seines, target the greatest breadth of functional diversity. These results indicate that using escape slot traps has the potential to lead to environmental improvements. However, the potential ecological benefits from escape slot traps are muted because two-thirds of the functional entities released by the escape slot traps are targeted by other gear types. The redistribution of conservation gains suggest that switching to escape slot traps is not likely to be beneficial to the coral reef ecosystem unless some other gears are simultaneously excluded from the fishery. These results call for caution when assessing ecological implications of gear-based conservation innovations particularly in gear-diverse coral reef fisheries where there are competitive interactions between gears.

Introduction

Gear-based fisheries management has become a popular strategy for managing coral reef fisheries in many developing countries (Condy et al 2014, Johnson 2010, Larocque et al 2012). Under this management strategy, resource managers mainly restrict the use of certain gears to protect specific sizes and species of fish (McClanahan & Mangi 2004). However, in instances where restricting the use of certain gear results in a large increase in the number of fishers using another type of fishing gear, resource managers opt to modify existing gears instead of outright prohibition (Milton et al 2009). This form of gear based fisheries management has received strong support from resource users because it allows the use of their existing skills and local knowledge during transition to the new gear (Condy et al 2014). Modifying existing gears also eliminates extra costs incurred on training especially when fishers transit to new gears (Mbaru & McClanahan 2013).

Existing research on gear based management approaches only relates different gear types and catches composition (sizes, species diversity and selectivity) to generate management recommendations aimed at maintaining fish populations (Dalzell 1996, Gobert 1994, Mangi & Roberts 2006, McClanahan & Mangi 2001, McClanahan & Mangi 2004, Pet-Soede et al 2001). For example, previous research on escape slots has shown that escape slots can be effective in reducing catch of juveniles and narrow-bodied species (i.e. bycatch) (Gomes et al 2014, Johnson 2010, Mbaru & McClanahan 2013). Although these assessments provide valuable insights on ecosystem impacts of non-selective fishing, the growing interest in an ecosystem-based approach has stressed maintaining and sustaining ecological functions (Sinclair et al 2002, Tillin et al 2006).

Choosing relevant functional traits and the complementary roles of organisms has become the cornerstone of functional ecology (McGill et al 2006, Violle et al 2007). By considering biological traits as proxies for function, the emerging functional trait-based approach can help uncover ecosystem processes and functional implications of changes in fisheries assemblages (Mouillot et al 2013, Villéger et al 2017). Trait-based approaches were initially applied in plant ecology (Cornwell et al 2006) and are now widely used across other organisms, such as birds (Naeem et al 2012), bats (Norberg 1994), corals (Darling et al 2012), insects (Poff et al 2006), and fish (Mouillot et al 2011), to provide key insights into the functional structure of assemblages. The approach has proven to be exceptionally versatile, offering insights into changes in assemblages through time (Friedman 2009, Villéger et al 2011), the impacts of species invasions (Corbin & D'Antonio 2010, Olden et al 2006), and responses to environmental change (Graham et al 2015, Laughlin et al 2011).

Several studies have used functional traits to assess how fishing modifies aquatic ecosystems based on in situ observations in temperate countries (Guillemot et al 2014, Koutsidi et al 2016, Tillin et al 2006). However, more remains to be understood about the functions that are being removed from the ecosystem by fishing, which is particularly important for the many multi-species fisheries in vulnerable tropical ecosystems. Consequently, linking different fishing gears to declines in targeted species and their ecological function remains unclear. In multi-species coral reef fisheries, fishing gears are known to exhibit some degree of overlap in the species they capture (McClanahan & Mangi 2001) and to reduce fish biodiversity (McClanahan 2015) highlighting the need to understand how competitive interactions among gear types affect outcomes (McClanahan & Kosgei 2018). Yet, only limited empirical attempts quantify overlaps in gear selectivity (McClanahan & Kosgei 2018).

Here I employ a trait-based approach to assess the functional selectivity of escape slot trap. I then compare selectivity patterns against six other fishing gears, many of which are commonly used in small-scale coral reef fisheries around the world. Specifically, I ask the following questions; (i) do escape slot traps target specific functional traits that could potentially affect reef ecosystems, and (ii) are there overlaps in trait composition between escape slot trap and other gears?

Material and Methods

Study sites and catch sampling

I used catch data on fish assemblages from 25 coral reef and lagoon sites conducted monthly between 2010 and 2016 in Kenya. (Fig. 5). Onsite observers identified landed catch to species level and recorded the number, size (total length in cm), gear used, landing site name, and date. Although all sampling was conducted during daylight hours, these include catches attributed to nighttime fishing activities as observers also intercepted fishers returning from their overnight fishing. At least 8 days of data collection was achieved every month, translating into a total of 599 sampling days over the survey period. To avoid potential misidentification, I excluded 60 species that were represented by only one individual in each gear. My analysis is based on 19,401 fish representing 245 species from 25 families, with a mean ± SD of 777 ± 546 fishes per site. I produced cumulative frequency curves to determine whether enough samples were collected to reach asymptotes of observed functional entities. All curves reached saturation as evidenced by the asymptote plateaus in the number of functional entities suggesting that my sampling for each gear was adequate (Fig. 10). Consequently, adding more samples of fish should not affect my results.

I assess functional selectivity to determine whether escape slot traps are associated with certain traits. To determine the potential for ecological impact of escape slot traps, I quantified relative differences in functional selectivity between escape slot traps and other gear types (i.e. basket trap, hook and line, speargun, gillnet, beach seine, and other nets).

Apart from gillnet and beach seine, occasionally artisanal fishers use a variety of other nets such as ringnets, scoop nets, cast nets, and mosquito nets; I therefore include a separate gear category of ‗other nets'. Gillnets and beach seines were prioritized over other nets because they are more frequently used.

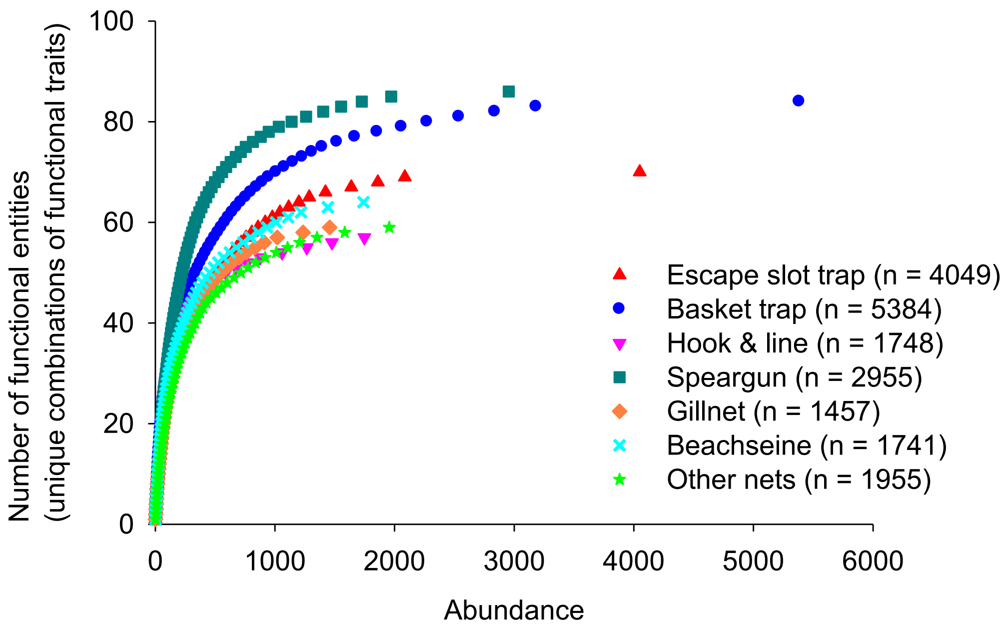


Figure 10. Cumulative frequency curves of the number of functional entities (i.e., unique combinations of functional traits) present in sampled fish assemblages per gear. Sample sizes are displayed in parenthesis.

Associations of gears with functional traits

Fish species were assigned to a set of categorical functional trait values relating to their diet, body-size, mobility, time of activity, schooling behaviour, and position in the water column. These ecological traits are key for determining trophic role and have been used in other studies examining functional diversity, vulnerability, and redundancy on fish assemblages in tropical ecosystems (Micheli et al 2014, Mouillot et al 2014). Based on main items consumed, I characterized diet into seven trophic categories: macroalgal herbivorous (i.e., fish eating large fleshy algae and/or seagrass), carnivorous (including fish and cephalopods), invertivorous targeting mobile invertebrate (i.e., benthic species such as crustaceans), herbivorous-detritivorous (i.e., fish feeding on turf or filamentous algae and/or undefined organic material), omnivorous (i.e., fish for which both vegetal and animal material are important in their diet), invertivorous targeting sessile invertebrates (i.e., corals, sponges, ascidians), and planktivorous (i.e., fish eating small organisms in the water column). Period of activity had three ordered categories: nocturnal, both diurnal and nocturnal, and diurnal. I categorized mobility based on three ordered subgroups: mobile within a reef, sedentary (including territorial species), and mobile between reefs. Schooling was coded using five ordered categories: large (>50 individuals) groups, medium (20-50 individuals), small (3-20 individuals), pairing or solitary. Vertical position in the water column was coded using three ordered categories: bentho-pelagic, pelagic, and benthic. Fish size was coded using six ordered categories: 0-7 cm, 7.1-15 cm, 15.1-30 cm, 30.1-50 cm, 50.1-80 cm, and >80 cm (Mouillot et al 2014).

Each unique combination of these six traits is considered a distinct functional entity (which may be comprised of one or more species) (Mouillot et al 2014). For example, of the 245 species sampled, I derived 163 unique functional entities. Associations between functional traits and fishing gears (based on abundance data) were examined using Principal Component Analysis (PCA) based on fourth root transformation of Wisconsin double standardized data. In this standardization, the fourth root of each element is calculated after each element is divided by its column maximum and then divided by the row total. This standardization is recommended for ordination of species data that exhibit substantial differences in sample sizes across sampling units (Legendre & Gallagher 2001).

Functional structure

A trait-based ordination analysis was used to describe variation in fish assemblage functional structure among gear types. To build a multidimensional functional space (Mouillot et al

2013), I performed a Principal Coordinates Analysis (PCoA) using a functional entity x traits matrix. Functional entity coordinates on the first four principal axes (PC) of this PCoA were used to construct a synthetic multidimensional ordination based on pairwise Gower‘s distances between functional entities (Legendre & Legendre 2012) (Fig. 10). Gower‘s distances allows mixing different types of variables while giving them equal weight (Legendre & Legendre 2012). A square root correction for negative eigenvalues was applied for Euclidean representation of distance relationships among functional entities in order to avoid biased estimations of distances (Legendre & Legendre 2012). Although there is no rule to choose *a priori* the number of dimensions, spaces with higher dimensionality (i.e., with at least four dimensions) provide the best assessment of functional diversity (Maire et al 2015). I therefore selected *a posteriori* the first four dimensions of the ordination, keeping a manageable number that reduced computing time and allowed graphical representation.

I adapted three widely used functional ecology indices to describe how gears target specific functions: functional volume (FV), functional redundancy (FR), and rarely targeted functional entities (RFEs). I define FV for each gear as the proportion of the functional space the gear occupies relative to that of all fish caught (Villéger et al 2008). Functional redundancy (FR) is the mean number of individuals per functional entity. The RFE index is expressed as the proportion of functional entities that constitute less than 1% of catch (total number of individuals) within a gear. With n_p being the relative abundance of a functional entity in a gear, I express RFEs as the following ratio:

$$n_p = \frac{n_i}{N_g}$$

$$RFEs = \frac{FE - \sum_{i=1}^{FE} \min(n_p - 1,\ 1)}{FE}$$

N_g denotes the total number of individuals in a gear, FE the total number of functional entities, and n_i the number of individuals in a functional entity i (Mouillot et al 2014). I also compute the number of unique functional entities targeted by the different gear types.

Potential for ecological impact of escape slot traps

To determine the potential for escape slot traps to have an ecological impact, I used a number of approaches. Firstly, I determined the catch component being released by escape slot trap, relative to unmodified basket traps. This component is represented by the catch that was landed specifically by basket traps but not escape slot traps. Having identified the catch component being released by escape slot traps, I then examined whether or not other gear types are targeting this component. In so doing, I was able to determine specific gear types that could potentially benefit, constrain or even offset conservation outcomes associated with escape slot traps. All comparisons and overlaps are based on the number of functional entities, FV, and number of species.

When examining the number of functional entities targeted by the different gears, I found a very long tail in the distribution i.e., although each gear type caught dozens of functional entities, the majority of the catch was typically comprised of only a few functional entities. Consequently, I provide complementary analyses of the gear types by: (i) the entire catch, (ii) the dominant 75% (i.e. the catch making up the fewest functional entities), and (iii) the dominant 50% of the catch (i.e. the 50% making up the fewest functional entities).

I then quantified the dominant (i.e. 75% of catch) functional traits on the catch component that is not targeted by other gear types to determine key functional groups of fish that will be retained in the ecosystem with full conversion to escape slot traps. Secondly, I present proportions of the number of unique functional entities and rarely targeted functional entities across all gear types. This analysis was further expanded to include corresponding values of FV and number of species for the unique and rarely targeted functional entities.

I also computed the number of functional entities, FV, and number of species captured by pairs of escape slot trap and other six gears. The results were compared with pairs between basket traps and the other five gears. Overlap in composition of functional entities between gears was visualised using Venn diagrams based on all catch, 75% and 50% of catch. Because of the complexity in interpreting Venn diagrams with more than four elements, I only present numbers and proportions of overlaps from the resultant groupings. Functional volumes were computed as the percentage of total FV targeted by all gears from the first four dimensions of the ordination.

Robustness analysis

To determine whether my results are robust to the extent of categorization of functional traits, I reran all analyses using all combinations of five traits out of six. I avoided reducing the number of traits lower than five so as to retain important dimensions of the functional space defining fish niches (Mouillot et al 2013). As such, an over simplistic definition of functional entities was avoided. I further performed a crude categorization potentially inducing high functional redundancy (many species in each functional entities) whereas a fine categorization would lead to few species in each functional entity (Mouillot et al 2014). In this analysis, I reduced the number of categories for each trait and reran all analyses with 64 functional entities (crude categorization) instead of 163 (fine categorization). For, example, instead of using all six categories on body size, I reran the analysis testing the association between gears and three size categories. Specifically, I used the following crude categories: diet [invertivores (mobile benthos, sessile, and plankton), primary consumers (omnivores, detritivores, and herbivores), and piscivores]. Size classes (0–15 cm, 15.1–50 cm, and >50 cm), schooling behaviour [gregarious (>20 individuals), small groups (2–20 individuals), and solitary], mobility (mobile versus sedentary), period of activity (diurnal/diurnal-nocturnal versus nocturnal), and position in the water column (benthic/bentho-pelagic versus pelagic) (Mouillot et al 2014). To show the robustness of my findings, I present the distribution of functional entities contained in the entire catch, in addition to the number functional entities and species in 50, 75, and 99% of the catch considering the reduced number of functional entities for each gear. I also show the proportion of rarely targeted functional entities (see Appendix).

Simulated random assignment models

I tested whether the observed values of rarely targeted functional entities were significantly different from the null hypothesis that individuals are randomly distributed into functional entities. In each of the seven gears, I simulated a random assignment of individuals to functional entities while ensuring that each functional entity had at least one individual. I simulated 999 random assemblages for each gear, and, for each simulation, I computed the rarely targeted functional entities while the number of individuals and the numbers of functional entities were kept constant. Analysis relied on R packages *vegan*, *ade4*, *FD*, and *cluster* (version 3.4.5). Figures were plotted in R and sigma plot (version 11).

Results

Associations of gears with functional traits

Escape slot trap and basket trap targeted a majority of benthic herbivorous-detritivores moving with the reefs (e.g., rabbitfishes and parrotfishes) (Fig. 11). Sessile invertivores (e.g., wrasses and porgies) and diurnal species were largely captured by spearguns. A combination of other nets that largely includes ring nets and cast nets as well as hook and lines harvested species moving in large groups feeding on plankton (e.g., mackerels and jacks). Gillnet and beachseines were largely associated with pelagic species (e.g., mackerels and jacks).

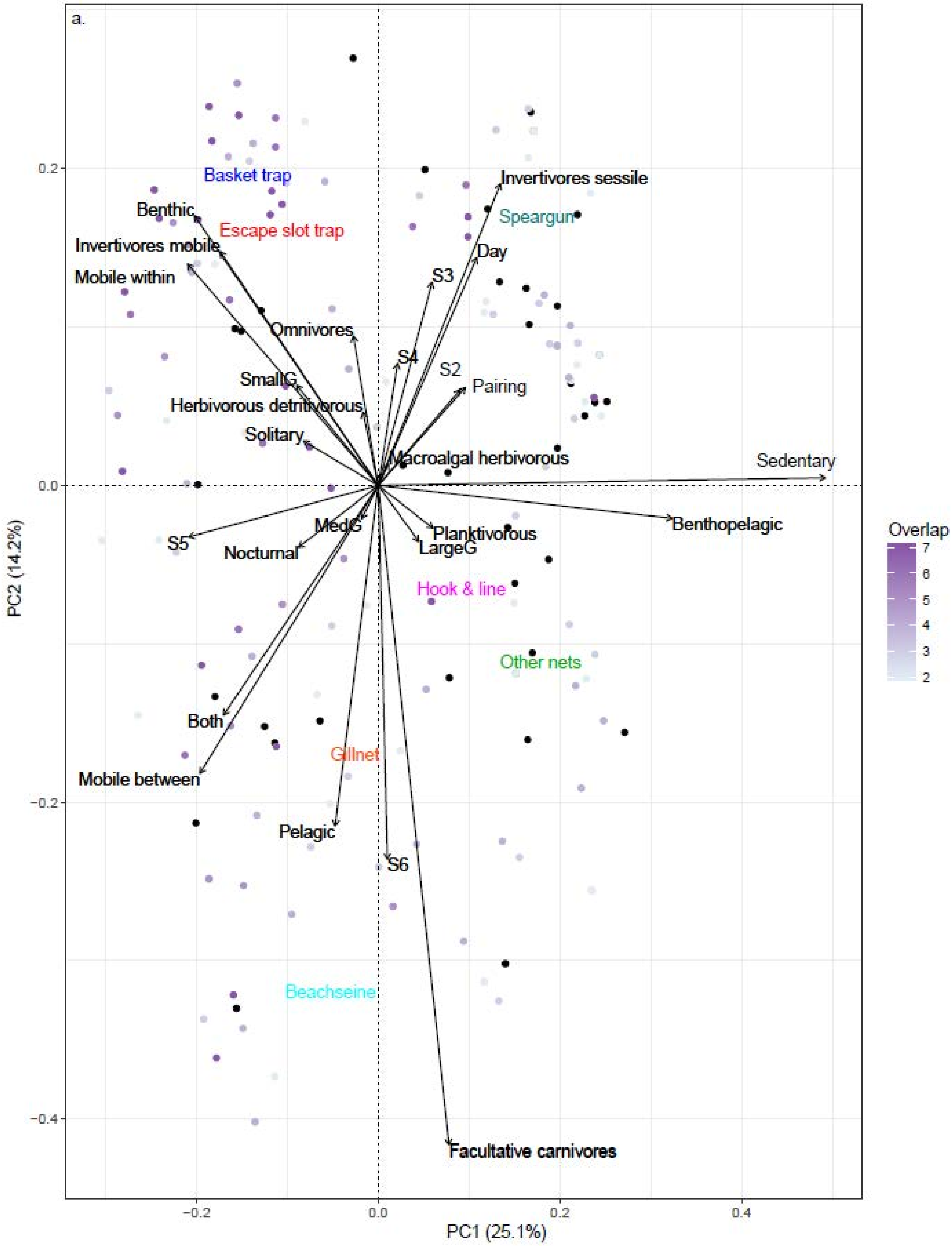


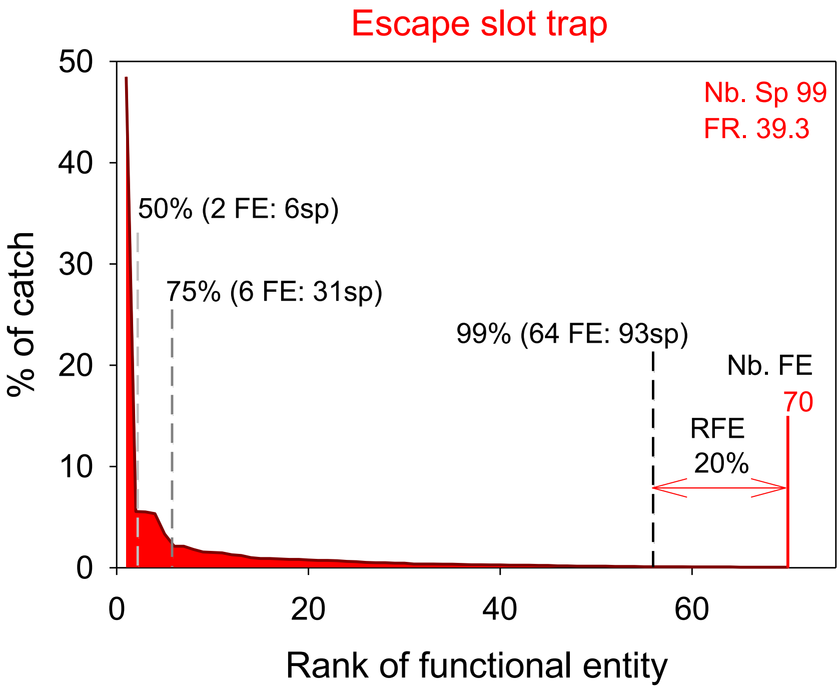
Figure 11. Principal component analysis of functional entities contained in the entire catch (n=163 functional entities). Coloured dots represent functional entities captured by the seven gear types analysed. Colour gradient represent functional entities shared across a range of gear combinations. Black dots represent unique functional entities targeted by a single gear. LargeG (>50 individuals) groups, MedG (20-50

individuals), SmallG (3-20 individuals) indicate size of fish schools. Fish size is coded using six categories: 0-7 cm (S1 – absent in my data), 7.1-15 cm (S2), 15.1-30 cm (S3), 30.1-50 cm (S4), 50.1-80 cm (S5), and >80 cm (S6). „Both" denotes species active during the day and night.

Patterns of association between gears and traits did not change much when considering the dominant 75% of the catch compared to those of all catch (Fig. A2a). For example, spearguns were consistently associated with diurnal species (Fig. A2a). However, in addition to herbivorous-detritivores, other herbivorous species that feed on macroalgae seemed to be predominantly harvested by traps (i.e., escape slot traps and basket traps). Considering 50% of the catch, all types of nets (i.e., gillnets, beachseines and other nets exhibited substantial similarities in trait composition (Fig. A2b). Substantial deviations in trait composition were observed between hook and line and spearguns. Considering the dominant 75 or 50% of the catch, other nets were consistently associated with pelagics (Fig. A2a & b).

Functional diversity

I detected substantial variability in the number of functional entities (functional diversity) targeted by gear types, ranging from 86 for spearguns to 57 for hook and line (Fig. 12). Distribution of individuals among functional entities is largely skewed with a few functional entities containing a large number of individuals, while the majority of functional entities contain relatively few (Fig. 12). Having shown that abundance is heavily packed in few functional entities across all gear types, I decided to compare functional diversity in the dominant catch, i.e., 75% and 50% of the total catch in each gear. Here, I show that escape slot traps host the fewest functional entities in 50% (2 functional entities; six species) and 75% of catch; hosting 6 functional entities representing 31 species (Fig. 12). The proportion of rarely targeted functional entities ranges between 11.9% for beachseine and 25% for basket trap, and observed values are all significantly higher than expected when abundance is randomly assigned to functional entities (Fig. 12; Fig. A3). Functional redundancy i.e., mean number of individuals per functional entity ranges between 39.3 in escape slot traps to 16.3 in gillnets (Fig. 12) with a species-functional entity gradient between 1.41 escape slot traps to 0.87 for speargun.



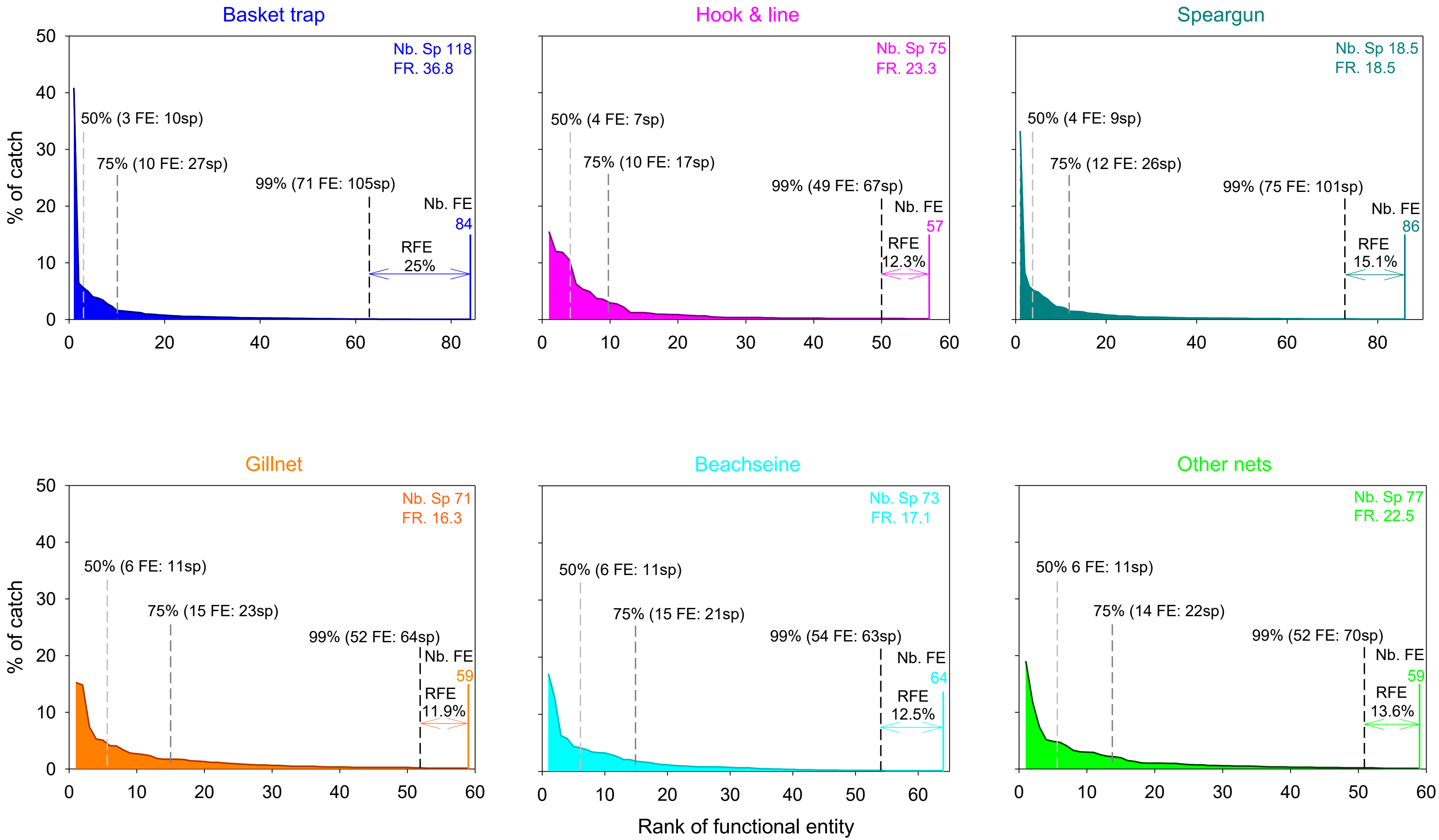

Basket trap
Nb. Sp 118
FR. 36.8
50% (3 FE: 10sp)
75% (10 FE: 27sp)
99% (71 FE: 105sp)
Nb. FE
84
RFE
25%
Hook & line
Nb. Sp 75
FR. 23.3
50% (4 FE: 7sp)
75% (10 FE: 17sp)
99% (49 FE: 67sp)
Nb. FE
57
RFE
12.3%
Speargun
Nb. Sp 18.5
FR. 18.5
50% (4 FE: 9sp)
75% (12 FE: 26sp)
99% (75 FE: 101sp)
Nb. FE
86
RFE
15.1%
Gillnet
Nb. Sp 71
FR. 16.3
50% (6 FE: 11sp)
75% (15 FE: 23sp)
99% (52 FE: 64sp)
Nb. FE
59
RFE
11.9%
Beachseine
Nb. Sp 73
FR. 17.1
50% (6 FE: 11sp)
75% (15 FE: 21sp)
99% (54 FE: 63sp)
Nb. FE
64
RFE
12.5%
Other nets
Nb. Sp 77
FR. 22.5
50% 6 FE: 11sp)
75% (14 FE: 22sp)
99% (52 FE: 70sp)
Nb. FE
59
RFE
13.6%
% of catch
Rank of functional entity

Figure 12. The distribution of fish individuals into functional entities is displayed for each gear type. The number of functional entities ("Nb FE.") present in each gear is shown at the bottom right of the distribution. Functional redundancy (FR) (i.e., mean number of individuals per functional entity) and number of species are displayed at far right top corner. The light grey dashed line illustrates number of functional entities contained in 50% of catch. The grey dashed line illustrates number of functional entities contained in 75% of catch while the black dashed line illustrates number of functional entities contained in 99% of catch. Rarely targeted functional entities (RFE) i.e., functional entities contained in 1% of total number of individuals captured in each gear is illustrated in double arrows displayed at far right bottom corner.

Functional space

The distribution of functional traits on the functional space shows that social grouping broadly changed from left to right along the first axis of the PCoA, whereas fish body-size and mobility increased from top to bottom along the second axis of the PCoA (Fig. 13). Herbivores, detritivores and omnivores, typically associated closely with the benthos, were positioned top-left in the functional space; sedentary, territorial and macroalgal herbivores were positioned middle right; paring invertivores targeting sessile invertebrates typically active during the day were positioned to the top right; invertivores targeting mobile invertebrates typically mobile within the reef in the top-right; planktivores in the middle-right; and larger carnivores that are largely pelagic and typically mobile across reefs were located in the bottom-left.

The first four dimensions of the PCoA cumulatively explained 47.5% of the projected inertia in the distribution of fish species traits (first two independent axes accounted for 29.7% of the variance). Explained variances are not more than 17% per axis (Fig 13). In examining the amount of functional space removed by the different gear types, I show that escape slot trap occupy the least FV of about 18% of the functional space whereas other gears occupy between 26 and 51%, considering the dominant 75% of catch. Nets in general (i.e. gillnets, beachseines, and other nets) filled more functional space (44.6-50.7%), but did so targeting relatively fewer species (71-77 species) than the escape slot trap.

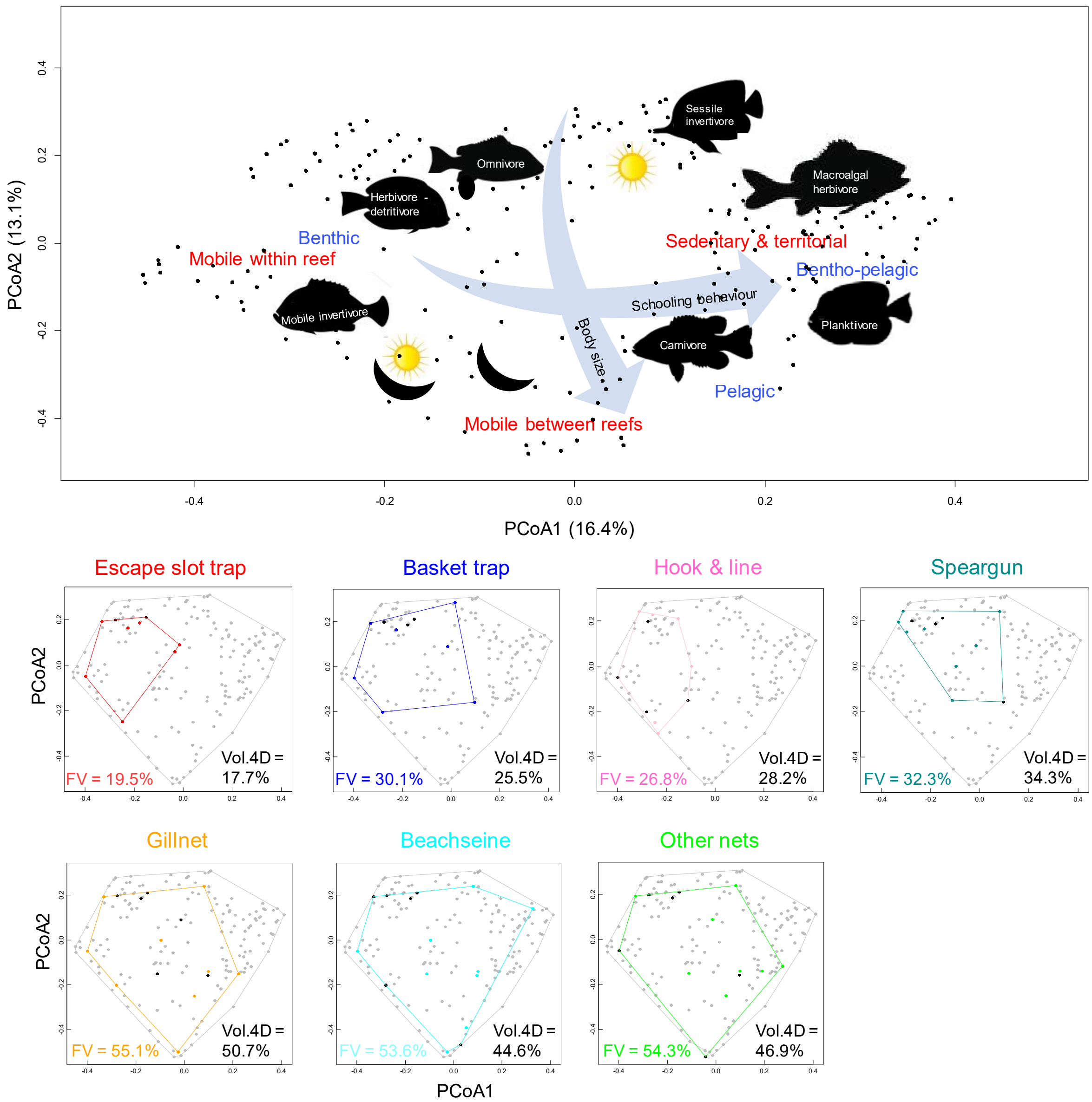


Figure 13. Distribution of functional entities is shown in functional space from a Principal Coordinate Analysis on functional traits based on all catch. 163 computed functional entities (black dots) plotted in the first two dimensions (four total) of functional space defined by six traits: body size (arrow indicating increasing body length), diet; mobility (red text); time of activity (sun and moon); social grouping (arrow indicating increasing size of fish school); and position in the water column (blue text). Illustrations and text show the position of average trait levels in the functional space. Distribution of functional entities is shown in functional spaces for each gear from a Principal Coordinate Analysis on functional traits (bottom convex hulls). Colour filled points are functional entities present in the catch of each gear while grey filled points are functional entities absent in the 75% catch of each gear. The total convex hull, including the 245 species split into 163 functional entities, is enclosed by grey continuous lines joining vertices of the convex hull that shape edges. Continuous coloured lines outline the functional volume (FV) determined by

coloured points representing the most abundant functional entities comprising 75% of the catch for each gear. Coloured text in the bottom convex hulls show FV for the first two dimensions whereas black text indicate FV considering all four dimensions. FV is expressed as a percentage relative to all fish caught. Black points are functional entities representing the most abundant functional entities comprising 50% of the catch for each gear.

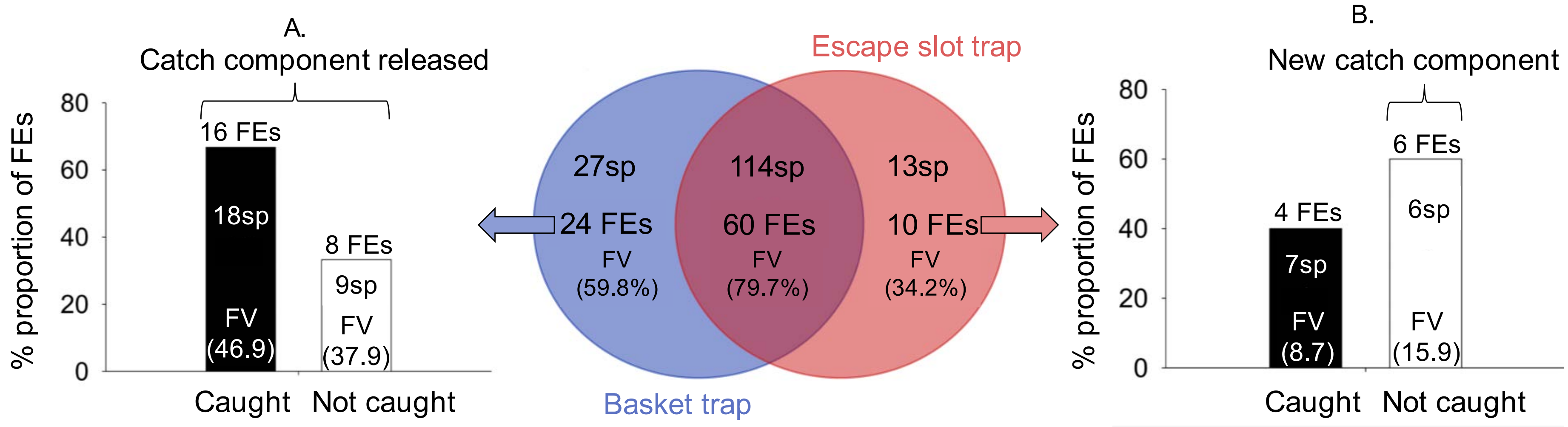
Gear overlaps

Basket traps and escape slot traps together targeted 94 functional entities although the two trap types share 60 representing 64% overlap. Of the 34 functional entities that were not shared by the two trap types, 24 were specifically caught by basket traps whereas only 10 were caught escape slot traps (Fig. 14). This means that escape slot traps release 24 functional entities representing 27 species – a catch component that can safeguard about 60% of assemblage functioning susceptible to trap fishing. Overlaps in gear selectivity indicate that two thirds (i.e., 16/24 functional entities) of the catch being released by escape slot traps is targeted by other gear types (Fig. 14). These overlapping functional entities carry about 47% of the total FV targeted by all fishing activities and about 59% of the FV that can potentially be removed by trap fishing. Zooming in across other gear types targeting the catch released by escape slot traps, I found that spearguns have the highest overlap, targeting 10 of the functional entities released by escapes slot traps. Of these, 5 (31.3%) are unique to spearguns, while five additional functional entities also overlap with hook and line and other nets. Hook and line and other nets independently target one and two functional entities respectively. Hook and line, gillnet, and beachseine together target the other three functional entities released. The one third that survives (8 functional entities) carry a FV of about 39% relative to all fishing activities (Fig. 14).

Full conversion to escape slot traps (all both basket traps are converted to escapes slot traps), targeted a new suite of assemblages representing six species, six functional entities, hosting 16% of assemblage functioning. Importantly, this new catch component represents a reduction of about 29% of the total FV affected by trap fishing if basket traps are used. Of concern is that partial conversion (where both basket traps and escapes slot traps were used in a site) led to an increase in the number of functional entities removed from six to 14. These new functional entities represented by 17 species affected more than 44.7% of assemblage functioning.

The four functional entities that were shared between escape slot traps and other gears host a mere 8.7% of the total FV affected by all fishing activities. Of the 14 functional entities that are only caught by the two trap types, differences in dominant traits emerge in terms of size, diet and schooling behaviour. Therefore, besides retaining smaller sized fish, other benefits associated with full conversion to escape slot traps is the retention of solitary species and fish feeding on mobile invertebrates (Fig. 14).

There were 19 functional entities that were commonly targeted by all the gears used in Kenya representing 12% of the functional diversity in this fishery. This shared component included 45 out of 245 total species, representing an 18% overlap among gear types. This catch component host 47.9% of the total FV targeted by fishing. Speargun had the highest number of unique functional entities (12) representing 49.2% of the FV removed by fishing (Table 11). Other gears caught between one (other nets) and eight (basket traps) unique functional entities potentially affecting up to 38% of assemblage functioning. Interestingly, unique functional entities associated with nets such as gillnets and other nets occupied the least amount of FV (<4%) (Table 13). Only escape slot trap and gillnet target unique functional entities that removed less than 20% of the total FV affected by fishing (Table 13). Turning to the FV present in the rarely targeted functional entities, escape slot trap targeted the least, i.e., 19.9%, all other gears targeted >22% of the total FV.



Basket trap: Dominant traits retained (8 FEs)

- Mobile invertivores
- 15 – 29 cm
- Solitary

*Partial conversion removes 44.7% of FV (14 FEs; 17sp)

Escape slot trap: Dominant traits retained (6 FEs)

- Sessile invertivores
- 30 – 44 cm
- Medium schooling groups

*Full conversion removes 15.9% of FV (6 FEs; 6sp)

Figure 14. Overlaps in catch composition between escape slot trap and basket trap. Venn diagram captures overlaps between the two trap types. Bar graphs (A and B) represent proportion of unique functional entities (FEs) targeted by the two trap types. Number of species, functional entities, and proportion of functional volume (FV) present catch component targeted by other gears for each trap type is shown as black bars. Empty bars show similar values for the two traps types but on the catch component that is not captured by other gears. Twenty-four functional entities captured specifically by basket trap represent the catch component being released by escape slot trap. Dominant traits in unique functional entities not captured by other gears are shown in boxes below bar graphs. Functional entities caught specifically by escape slot trap but absent in other gears denote new assemblage functioning targeted by trap fishing.

Table 13. Summary of number of species, functional entities (FEs), and functional volume (FV) on unique and least functional entities captured by each gear. Similar proportions are also presented for combinations of catch targeted by pairs of the two trap types and other gears.

					Pairs of trap types and other gears			
	Unique FEs		**Rarely targeted FEs**		**Basket trap**		**Escape slot trap**	
Fishing gear	No. FEs(species)	% FV	No. FEs(species)	% FV	No. FEs(species)	% FV	No. FEs(species)	% FV
Escape slot trap	**6(6)**	16	**6(6)**	19.9	**60(114)**	**66.4**		
Basket trap	8(9)	37.9	13(13)	48.8			60(114)	66.4
Hook and line	7(7)	21.5	8(8)	39.2	35(77)	67.2	28(66)	56.6
Speargun	12(12)	49.2	11(12)	55	52(102)	73.4	41(87)	57.1
Gillnet	3(4)	3.6	7(7)	22.2	32(72)	58	33(74)	60.4
Beachseine	7(9)	20.1	10(10)	53.2	34(67)	59.4	33(67)	55.3
Other nets	1(1)	-	7(7)	32.5	32(70)	53.1	28(66)	53.1

Highest proportions of FV present in the rarely targeted functional entities across gear types were however found in basket traps (48.8%), beachseine 53.2%, and spearguns (55%). Regarding pairing, results show that all pairs between the two trap types and the other five gears removed >60% of the total FV fishing regardless of the trap type. However, there were minimal reductions in FV for pairs between escape slot traps and other gears relative to those with basket traps (Table 13). For example, a combination of basket traps and spearguns removed almost the highest amount of FV (73.4%) that can potentially be affected by a pair of two gears. However, this proportion was reduced to 57.1% with the use of escape slot traps and speargun (Table 13).

Robustness analysis

Using the crude functional categorisations, the level of rarely targeted functional entities is surprisingly very close to that observed with a much finer categorization (Fig. A3 & A4). The observed distribution of abundance between functional entities is more right skewed than expected, with a long tail with few individuals (Fig. A4). Overall, my sensitivity analyses show the consistent and uneven distribution of some functional entities, whatever the number, the identity, and the categorization of traits. I also reran all analyses with all combinations of five traits out of six (Fig. A4). Whatever the combination, all patterns are still close to those observed with six traits (Fig. A4).

Discussion

Understanding the ecosystem impacts of conservation remains critical in the natural resource management context (Hughes et al 2017). In the fisheries context, understanding impacts of a fishing gear to the ecosystem is essential before making recommendations on whether or not a gear should be promoted, modified, restricted or banned (Hall et al 2000, Mangi et al 2007, Morgan & Chuenpagdee 2003). Here, a functional approach was used to examine potential ecological implications of a gear based conservation intervention (i.e. escape slot trap) in a multi-gear coral reef fishery. Unlike in previous studies, my analysis includes other gear types that often operate concurrently within the same ecosystem. In so doing, this analysis determines whether other gears could potentially complement, constrain or offset key ecosystem benefits associated with escape slot traps. Overall, I show that using escape slot traps has real potential to lead to environmental improvements. Fish assemblages in escape slot traps are more functionally redundant (tendency of species to perform similar functions) and a vast majority occupy the least functional volume (i.e., functional space occupied relative to that of all fish caught). However, given the extent of overlaps in gear selectivity, switching to escape slot traps may not achieve conservation targets in the Kenyan multi-species coral reef fishery unless certain gear types are excluded. Implications of the results are discussed in turn.

Traps account for about 40% of the total fishing effort in the Kenyan marine artisanal fishery (Mbaru & McClanahan 2013). Results of my analysis and those of previous studies confirm that fish assemblages captured in basket traps contain the highest number of species (Hicks & McClanahan 2012). However, in addition to high species diversity, I show that fish assemblages in basket traps have high functional diversity relative to all other gear types except speargun. These results alone can perhaps justify the need to regulate the basket trap fishery. Though the inclusion of escape gaps in traps was primarily meant to allow juveniles and narrow-bodied species (i.e. bycatch) to exit (Johnson 2010, Mbaru & McClanahan 2013). Here, I show that in addition to bycatch reduction, fish assemblages in escape slot traps are not only functionally redundant but a majority of the catch occupy the least FV compared to all other six-gear types. FV removed by unique functional entities is lower in escape slot traps compared to that of other gear types, except for gillnets. A combination of basket trap and speargun removes almost the highest proportion of FV (73.4%) relative to pairs between other gear types. This proportion is marginally reduced to a FV 57.1% if an escape slot trap is used with speargun. Only a hand full of new functional entities that account for a mere 8.7% of the total FV affected by fishing will be removed from the ecosystem if all basket traps were converted to escape slot traps. This represents a substantial reduction (22%) of the total FV that can potentially be removed by trap fishing. Apart from gillnet, all other gear types have more FV in the unique, and rarely targeted functional entities compared to that of escape slot traps. Switching to escape slot traps can also retain key functional groups of fish, i.e., smaller sized fish, those that feed on mobile invertebrates and are solitary in nature. Taken together, these results indicate that the inclusion of escape slot in traps can potentially lead to environmental improvements in terms of biodiversity protection and assemblage functioning.

Considering the extent of overlap observed across all gear, it is however unlikely for the Kenyan coral reef fishery to achieve sustainability if the status quo remains. Foremost, I showed that other gear types catch two thirds of the catch released by escape slot traps – a scenario that can potentially constrain ecosystem gains associated with the conservation intervention. No case can be made even on the one third that survives because the amount of FV targeted by other gears within the catch component released by escape slot traps (~47%) is higher than the FV that is removed when only basket traps are used (~38%). Testing the effect of using different combinations of pairs of gears in light of the conservation intervention, I found that using the two trap types concurrently (i.e., pairing basket traps and escape slot traps) removes the highest amount of FV (66.4%) than all other pairs between escape slot traps and other gear types. This means that having basket traps and escape slot traps within the same fishery (or any other combination of two gears) can easily offset conservation gains associated with escape slot traps because all pairs remove >60% of the total FV. This proportion surpasses by far the FV of 37.9% that trap fishing can potentially safeguard when only escape slot traps are used. It is also recognized that a combination of gillnet and escape slot trap can remove a slightly higher number of species and FV relative to basket trap and gillnet. Taken together, these results indicate that gear overlaps in selectivity are likely to constrain potential ecosystem benefits associated with gear-based conservation interventions such as escape slot traps (Condy et al 2014). In light of these findings, it is evident that escape slot traps can only make modest environmental improvements only if coupled with gear bans.

My functional approach unveiled key linkages among different fishing gears, species targeted, and their ecological function that could shape future assessments on ecological implications of fishing gear to the coral reef ecosystem. In almost all instances, there were very minimal differences in the number of species present among gears in the specific catch components analysed. However, clear differences were illuminated between gear types based on functional entities and FV. For example, comparison between basket trap and escape slot trap based on functional traits did not show any statistically significant difference in trait composition. Although in the broader context this finding may imply that the prime target species of basket trap and escape slot trap fishers remain fairly unchanged, the reality is much more complex. Indeed, I show that escape slot traps captured significantly fewer functional entities than basket traps and that their dominant catch occupies much smaller functional volume than basket traps. Relying on species or individual traits alone would have led to inconclusive findings on the differences in selectivity and the effect of different fishing gears on the marine ecosystem. Thus, these results collectively emphasize the importance of the functional approach in assessing the effect of fishing on assemblage functioning.

Previous studies have shown that species diversity, functional diversity, and assemblage functioning are intricately linked (Mouillot et al 2013, Villéger et al 2008). Here, I show that these relationships in fished assemblages are not linear. For example, I show that beachseine target slightly lower number of species than other nets yet had more functional entities that occupy slightly less FV. Escape slot trap had the third highest number of species yet had less functional entities compared to speargun that had more species. In addition, escape slot trap occupy the lowest FV compared to all gear types. This implies that capturing a high number species may not strongly contribute to loss of assemblage functioning as previously thought (Cumming et al 2006, Murawski 2000, Wackernagel & Rees 1998). The conclusion that massive erosion of species by highly species diverse fishing gears directly translates into outright depletion of ecosystem functions as we have thought before (Carpenter et al 2008, Hughes et al 2003, Knowlton & Jackson 2008) deserves further investigation. I also recognize that functional volume removed by unique functional entities and rarely targeted functional entities can significantly amplify the effect of specific fishing gears on assemblage functioning. This potential compounding effect is manifested in fish catches among basket trap, hook and line, speargun, and beachseines. This means that reduction of selectivity even at a lower threshold can potentially lead to substantial alteration in assemblage functioning.

Conclusion

I highlight the viability of escape slot traps as a sound fisheries conservation tool in coral reef fisheries. However, I highlight critical competitive interactions that could undermine the potential ecological impact of escape slot traps in coral reef ecosystems. Focusing on one gear, and showing how that gear impact ecosystem functioning of environment may be insufficient as other gears may constrain or even offset the anticipated ecosystem gains. In areas where this conservation intervention is embraced, I recommend total conversion to escape slot traps for the real environmental impact to be felt in the long term. In this fishery, nets, including gillnets and beachseines, target the greatest breadth of functional diversity. Prohibiting spearguns would effectively double the number of functional entities not affected by trap fishing. In light of this information, I therefore support the prohibition of beachseine and speargun in Kenya because increased usage of these gears can have far reaching ramifications in terms of eroding functional diversity in the coral reef fishery.

Chapter 7: General discussion

This thesis contributes knowledge and further understanding on how conservation innovations diffuse among people, affect people's wellbeing, and their potential to contribute to ecological sustainability. Prior to this thesis, a major gap existed in integrating network science in the study of conservation diffusion. Although there have been methodological guidelines (Pietri et al 2009, Ramirez-Sanchez 2011b), empirical studies are rare and results have often been inconclusive. Here, I contribute to this body of work by integrating decades of social science theory on diffusion of innovations with novel breakthroughs in social network analysis to offer a clearer understanding of the factors that shape conservation diffusion over time, using a case study of a conservation-oriented fishing gear modification in Kenya. I then draw on social network theory and methods to develop specific criteria for selecting key stakeholders to facilitate diffusion related conservation objectives. Additionally, a second major gap existed in that studies that analysed consequences of conservation suffered from lack of methodological robustness and rarely pointed to clear cut arguments about net outcomes (Beauchamp et al 2018a, Biedenweg & Gross-Camp 2018). The second half of the thesis evaluates consequences of adopting this conservation by: (i) demonstrating how adoption or non-adoption of conservation affect people's wellbeing; (ii) by showing whether adoption of conservation can potentially lead to environmental improvements. Together, findings of this study substantially increased our understanding on the factors that shape adoption patterns in conservation diffusion, key players in conservation diffusion, and the social and environmental consequences of conservation diffusion.

Summary of the findings

Gap 1: Limited studies have examined the effect of social networks on the conservation diffusion process

I addressed this gap in chapter 3 using emerging tools in network analysis that explore the combined effect of social networks and socioeconomic factors (i.e., personal and socioeconomic status attributes) on diffusion processes (Lusher et al 2013, Wang et al 2014). I found that network processes to a large extent contributed to adoption, particularly during the early stages of the conservation diffusion process. By showing that communication behaviour (measured via social network) is a strong predictor for early adopters, my results seem to challenge a long-standing notion in diffusion research that communication behaviour is key for late adopters (Rogers 2010, Valente 1996b)

My two-step modelling approach in the longitudinal analysis of conservation diffusion yielded three additional key findings that depart from traditional views, as highlighted below. Firstly, my initial regression framework including a wide range of socioeconomic factors (i.e., personal and socioeconomic status attributes) showed a number of socioeconomic factors that were important for early and late adoption. However, by integrating social networks in the analysis, only a constricted range of socioeconomic status attributes emerged as important predictors of adoption behaviour over time. All personal attributes (i.e., traits that revolve around perceptions) were no longer significant when social networks were taken into account – perhaps emphasising the point that social networks can play a major role in moderating some personal attributes that may act as barriers and/or drivers for adoption (Greiner et al 2009).

Secondly, there were minimal differences in socioeconomic status attributes between early and late adopters when social networks were taken into account. This finding also seems to challenge the longstanding theory of diffusion, which argues that a wide range of socioeconomic factors tend to distinguish early and late adopters (Barham et al 2004, Läpple & Van Rensburg 2011, Rogers 2010). Here, I instead provide evidence suggesting that socioeconomic status attributes that distinguish between early and late adopters may not be as broad as previously thought once social networks are accounted for.

Thirdly, I did not find a direct node-to-node network contagion effect; instead, I showed that the adoption status of network partners in strong cohesive groups had significant effects on early adoption. This suggests that network clusters can provide more efficient injection points in complex contagion process such as the one studied here. These findings further advance our understanding of the role of communication behaviour in diffusion processes in the context of conservation and beyond. I highlighted two key observations that could have possibly contributed to these surprising results. First, my research explicitly measured communication behaviour rather than relying on proxies, as has been the case in previous research (Rogers 2010). Second, my study relies on data from fishers who are known to display peculiar habits (e.g., being risk seekers) and therefore may not be representative of the general population (Cinner et al 2010). In other words, findings might be specific to this particular intervention and the social-ecological setting, and should therefore be generalized with care.

Implications for conservation: In the Kenyan context, findings from this analysis should be taken into account to increase uptake of escape slot traps through target populations. Beyond the Kenyan case study, my findings strongly suggest, that for policy measures to be effective in dissemination of conservation interventions, localized social cliques can be harnessed to provide critical injection points to jumpstart conservation diffusion processes. Considerable waste could be avoided in conservation diffusion processes if resources are invested in early adopters that are influential to other potential adopters as demonstrated by my findings.

Gap 2: No specific criteria exist for selecting key stakeholders to facilitate more widespread adoption and diffusion of conservation interventions

In chapter 4, I addressed this gap by identifying key socioeconomic factors associated with individuals that are ideally placed to facilitate four distinct diffusion related conservation objectives (i.e., key players): (1) rapid diffusion of conservation information, (2) diffusion between disconnected groups, (3) rapid diffusion of complex knowledge or initiatives, and (4) widespread diffusion of conservation information or initiatives over a longer time period. A key finding here was that depending on the conservation objective, different socioeconomic factors were more or less important for selecting key players. This means that the inclusion and/or exclusion of certain stakeholders can, and should be tailored to the specific conservation goal at hand when conservation programs are rolled out.

Having identified the key players (i.e., individuals identified using social network analysis) for the four distinct diffusion related conservation objectives, I then tested the framework to investigate whether the socioeconomic attributes of the key players I identified match the ones typically selected to facilitate conservation diffusion (i.e., current players). Results show considerable discrepancies between current players and key players. I highlighted potential misalignment of effort and missed opportunities for progressing more effective conservation diffusion. Essentially, this could be one reason sustainability goals have been difficult to achieve, at least in the Kenyan context where this empirical work was conducted.

In addition to aligning specific stakeholders to specific conservation objectives, my findings also demonstrate the value of network science in disaggregating the two-step flow diffusion model in the conservation context (Nisbet & Kotcher 2009). Disaggregating the diffusion related conservation objectives showed that different socioeconomic factors emerge as important in selecting key players to achieve certain conservation objectives instead of others. Coarsely aggregating all diffusion related conservation objectives as one diffusion process would have led to the conclusion that all conservation diffusion processes are equally influenced by individuals exhibiting certain socioeconomic factors. The sort of conservation diffusion strategy advocated here has the added benefit of being somewhat less vulnerable to fragmentation even if the role of one type of stakeholder is lost or ineffective (Borgatti & Foster 2003).

Implications for conservation: Investing in the right stakeholders as specialized communication channels can potentially lead to more progressive and effective conservation diffusion processes. Using key players in conservation diffusion can potentially save conservation practitioners a great deal of time, effort, and financial resources that are currently lost when resources and efforts are misaligned to certain stakeholders that are not ideally placed to influence the masses as highlighted in the Kenyan case study.

Gap 3: Little understanding of the impact of conservation diffusion on people

I addressed this gap in chapter 5 by evaluating outcomes of conservation using the multidimensional wellbeing framework (Gough & McGregor 2007). The design of this chapter was guided by a BACI (before-and-after control intervention) framework that combined controls with baselines. Precisely, I wanted to know whether wellbeing outcomes differ among adopters relative to non-adopters of escape slot traps and controls (i.e., villages where escape slot traps were not introduced) over time. Across multiple domains of wellbeing, I found no evidence that adoption did any harm to people that adopted. Indeed, there were modest improvements in material and subjective livelihood wellbeing for adopters of the escape slot trap over time. The variations I found in wellbeing experiences (in terms of magnitude of change) among adopters, non-adopters, and controls across the different domains over time affirms the dynamic and social nature of wellbeing. The alternative approach in evaluating relational wellbeing using an indicator of relational balance (i.e., reciprocity - tendency that two people that are connected speak to each other) as captured in the network theory, can potentially challenge the traditional approach on how relational wellbeing has been conceptualized in impact evaluation research (Chapter 5). Findings provide a more holistic picture of the consequences of conservation diffusion processes on human associated communities.

Implications for conservation: On the Kenyan case study, findings suggest that the intervention studied satisfies the cardinal rule for environmental policy makers that conservation should at the very least do no harm to the local populations affected by interventions (Biedenweg & Gross-Camp 2018). At a time when fisheries conservation interventions face a legitimacy crisis (Finkbeiner et al 2017), my evaluation provides wider legitimacy and support towards marine biodiversity conservation efforts particularly in rural economies where adoption of conservation interventions remain a fundamental challenge. Beyond the Kenyan case study, findings emphasize the need for environmental policy to use multiple indicators of wellbeing in addition to baselines in future evaluation research.

Gap 4: Linkages between use of conservation-friendly fishing technologies and assemblage functioning is still unclear

In chapter 6 I employed a functional trait-based approach to connect traits to fishing gears in multi-species coral reef fisheries (Mouillot et al 2013). Here, I wanted to determine whether escape slot traps (the conservation intervention studied in my previous chapters) remove and potentially compete with other gears for fishes with unique combinations of functional traits (functional entities). Across all gears, I found that escape slot traps target the least breadth of functional diversity, potentially affecting the smallest volume of assemblage functioning (Chapter 6). From an ecological viewpoint, these findings indicate that the escape slot trap can be a viable conservation tool in coral reef fisheries (Sinclair et al 2002, Tillin et al 2006). However, considering the extent of overlap in trait composition between escape slot trap and other gears - especially in the dominant catch – my analysis suggests that other gear types can potentially constrain or offset key ecosystem benefits associated with escape slot traps (Chapter 6). In the present case, this finding indicates that switching to escape slot traps (i.e., adopting the intervention) may not achieve conservation targets in the Kenyan multi-species coral reef fishery if the status quo in terms of gear utilization prevails.

By disaggregating catch into proportions, I found that unique and rarely targeted species in fished assemblages carried a higher proportion of functional diversity even for some selective gears such as hook and lines and spearguns. The minimal differences I found in functional diversity across gear types based on total catch and dominant catch suggest that total catch might provide weak insights on differences in gear selectivity whereas dominant catch alone cannot be used as a broad-scale indicator of potential impact of fishing on assemblage functioning. These findings could shape future assessments on ecological implications of fishing in multi-gear and multi-species fisheries.

Implications for conservation: These findings highlight the need to manage fishing of rare taxa with potentially important ecological functions because overfishing these species can potentially lead to substantial alteration in assemblage functioning. Future conservation priorities in coral reef fisheries should include monitoring of other gears such as hook and lines that are traditionally assumed to be selective, especially on the type and size of hooks used. This recommendation is supported by my findings that showed reduction of selectivity even at a lower threshold could significantly alter assemblage functioning (Chapter 6). Findings further reemphasize the need to restrict or regulate the use of spearguns among other less selective nets such as beachseines (McClanahan & Mangi 2004). Policy makers advocating for the upscaling of conservation interventions should equally consider other intervening or broader contextual factors that can capture the benefits of interventions, that can render conservation efforts ineffective.

Cross-cutting insights on diffusion of innovations theory

Potential spillover of benefits

Within experimental sites (i.e., where the escape slot trap was introduced), I observed some degree of similarity in wellbeing conditions between adopters and non-adopters (Chapter 5). Spillover of conservation gains (benefits) within experimental sites is the most likely explanation for this finding (Chapter 5), which is supported by my ecological analysis (Chapter 6). Specifically, I found that two thirds of the fish assemblages released by escape slot traps are actually harvested by other gear types, including those that used unmodified basket traps (Chapter 6). In other words, conservation and associated economic benefits of using escape slot traps (the intervention) within experiments were largely passed on to fishers using other gears, suggesting potential spillover of benefits to other trap fishers that did not adopt the escape slot trap.

Diffusion research stresses the need to analyse consequences of innovation adoption (Rogers 2010). As mentioned previously, adjustments to the diffusion of innovations theory has narrowed down the list of categories for adoption consequences to public vs. private goods (Miller 2018, Wejnert 2002). Private goods are benefits associated with one party and not available for others, whereas public goods are benefits associated with the entire social system (Sable & Kling 2001). It is against this background that this thesis endeavoured to analyse the social and environmental consequences of the conservation intervention. The double prong examination of the consequences of conservation diffusion on people and the environment not only demonstrated the intricate links between the two domains, but also illustrated how benefits or costs are reflected among target population.

Asymmetric importance of social networks

Social networks can capture both the quantity and quality of social relationships among individuals (Borgatti et al 2009). In this study, I integrated social networks to better understand factors that influence conservation diffusion (chapter 3), identify key stakeholders to facilitate conservation transfer (Chapter 4), and investigate the consequences of conservation diffusion on people‘s wellbeing (Chapter 5). My novel examination of the combined effect of personal attributes, socioeconomic status, and social networks on conservation diffusion affirmed that adoption behaviour can be more socially constructed as a product of endogenous network processes (i.e., network position, network structure, and social influence) and exogenous socioeconomic factors (e.g., personal, sociodemographic, or socioeconomic status attributes) (Chapter 3). Drawing from the theoretical foundations of various centrality measures described in network science, I disaggregated conservation diffusion processes into four distinct conservation objectives (Chapter 4). Different socioeconomic factors emerged as important in selecting ‗key players‘ to achieve certain conservation objectives instead of others - suggesting that implementation of conservation goals is highly context-specific and cannot be generalized (Chapter 4). Guided by the recent literature that highlights the intricate link between reciprocity and social relational balance (Tóth et al 2018), I compared the number of reciprocated social network ties (an indicator of relational wellbeing) (Chapter 5) between adopters of the escape slot, and non-adopters within experiments and control villages where the conservation intervention was not introduced. Variations in the magnitude of change among adopters, non-adopters, and control villages were not statistically significant over time, highlighting that neither the presence of the intervention in experimental villages nor adoption of the escape slot trap was sufficient to significantly reshape social relationships among fishers studied (Chapter 5).

Findings from the three chapters clearly demonstrated the value of the network approach in interdisciplinary research such as the current study. Future diffusion studies can integrate the network processes adopted in chapter 3 to better understand how social networks relate to behaviour change. Beyond conservation diffusion, the framework for selecting key players I developed in chapter 4 can be applied in many research and intervention areas, such as community development studies, participatory research, community intervention, and behaviour change to mitigate the problem of stakeholder identification in ways that avoid blueprint approaches. The network property used in chapter 5 (i.e., reciprocity - tendency that two people that are connected speak to each other) deemphasizes the numeric properties of social networks, and can be applied to any evaluation design regardless of the intervention or the number of network nominations made by a respondent.

Potential interaction between innovation consequences and dis-adoption

Although my examination of the consequences of adoption showed no harm on the people that adopted (Chapter 5), about 16% of the adopters abandoned the use of the escape slot trap after some time (Chapter 3). In theory, personality traits, socioeconomic status, and communication behaviour (e.g., position in the network) can be associated with dis-adoption, as I found here (Chapter 3). However, diffusion of innovation theory also argues that changes that occur to an individual as a result of adopting innovations could be the ultimate arbiter to determine whether or not people maintain innovations over time (Rogers 2010). The minimal improvements that were observed in some domains of wellbeing and the lack of clear cut “losses” on the part of adopters (that can be attributed to the intervention) can perhaps explain the large number of fishers that maintained the use of escape slot traps over time relative to those that dis-adopted. However, the lack of substantial gains in wellbeing conditions among adopters over time could perhaps provide an additional explanation for dis-adoption in this diffusion process (Chapter 5).

Indeed, my ecological analysis found that other fishers including basket trap fishers (i.e., non-adopters who did not modify their traps) to a large extent benefited from the presence of the intervention by harvesting part of two-thirds of the catch released by adopters of escape slot traps (Chapter 6). This indicates that adopters could lose out in terms of catch quantities to fishers who decide not to adopt the escape slot trap. By uncovering these interactions on catch landed between adopters and other fishers (including those that did not modify their traps), perhaps an additional explanation can be found for dis-adoption in this diffusion process. This situation effectively implicates the absence of adequate enforcement capacity as a possible reason for the poor rates of success even in well-designed conservation strategies with a high degree of legitimacy (Bergseth & Roscher 2018). Thus, policy discussions and actions that overemphasize the need to scale up conservation interventions should concurrently prioritize empirical investigations of the underlying local dynamics that can potentially undermine adoption and diffusion processes.

Emerging themes on diffusion of innovations theory

Diffusion process can be similar in multiple social systems

I observed consistent adoption rates and patterns across all experimental villages where the escape slot trap was introduced (Fig. A5). Adoption trajectories (i.e., diffusion process) show asymptote plateaus on the S-shaped curves sixteen months after inception of the intervention (Fig. A5). Rate of adoption has precipitated interests from researchers because people do not always adopt innovations at the same time (Rogers 2003). In theory, different social systems could adopt a single innovation either similarly or differentially (Boyne et al 2005). Different innovations could also be adopted either similarly or differentially within a single social system (Van Slyke et al 2004).

This study investigates a diffusion process based on a single innovation across four fishing villages. Though the fishing villages may be contextually similar (i.e., all represent social-ecological settings dominated by fishing communities), they cannot be assumed to be entirely identical in terms of socioeconomic conditions (Chapter 2). Moreover, respondents from the four fishing villages exhibited different socioeconomic conditions as demonstrated by their variations in communication behaviour (social networks), personal, and socioeconomic status attributes (Chapter 3, 4, and 5). Yet, despite this diversity in socioeconomic conditions across the multiple units of analysis, diffusion processes were almost identical across all sites. Evidence now exists that shows diffusion processes for a single innovation can be similar even in different social systems where participants exhibit different socioeconomic conditions.

Right communication channels can make a difference in diffusion process?

In the present diffusion process, the same implementer introduced the intervention across all four fishing villages. Although the four fishing villages are organized as beach management units that sometimes engage in collective conservation actions (Chapter 2), there was no collective adoption at the village level. In other words, adoption was largely an individual decision though some degree of social influence was observed within cliques (Chapter 3). The time taken (i.e., sixteen months) to achieve stability in the diffusion process such as the one studied here may or may not be ideal depending on the type of innovation to be diffused or the objective of the diffusion process (Fig. A5). For example, some conservation interventions may require rapid uptake especially in cases where certain species or habitats under emergency threat need protection (Haddow et al 2013, Kapucu 2008).

Previous empirical studies on adoption rates have shown that 49 - 87% of the variance in rate of adoption is explained by perceived attributes of an innovation[14]. Thus, it is important to

[14] Initial studies identified five characteristics innovations that determine their rate of spread, i.e., relative advantage, complexity, trialability, observability compatibility (Rogers 1995). These characteristics are perceived qualities of innovations either relative to the existing ideas they supersede, or whether their attributes are consistent with the existing values and needs of potential adopters, or whether their nature are easier or difficult to use, or whether their use can be experimented with on a limited basis or whether their adoption effects can be observed by others (Rogers 1995). However, given the increasing diversity of innovations in recent times, other characteristics such as flexibility, riskiness, and stickiness factor of innovation have also been used in some cases to explain patters of adoption for some unique social and technological innovations (Gladwell 2006).

note that adoption of the escape slot trap innovation could have also been influenced by several attributes of the innovation highlighted in the diffusion of innovations literature, such as complexity and relative benefit (Rogers 1995). Since my study examined a single innovation, these factors would have essentially been held constant in my analysis. Future studies examining, for example, escape slot traps with differing levels of complexity, would be required to explore the influence of these attributes on the adoption of these traps.

In addition to these attributes, other variables such as the nature of the social system, type of innovation decision[15], nature of communication channels, and extent of change agents‘ promotion efforts affect the relative speed with which an innovation is adopted (Rogers 1995). Being a single innovation that was adopted in a similar way across all social systems, not much can be done on the intervention itself (other than re-invention) and the social systems to affect the relative speed of adoption. However, possible readjustments can be made on the ―nature of communication channels" and ―extent of change agents‘ promotion efforts" in light of the diffusion of innovations theory. By highlighting potential misalignment of effort and missed opportunities in the current stakeholder engagement process in Kenya (Chapter 3), a key question emerges. Can adjustments to the ―nature of communication channels" increase the rate of adoption of a single innovation in social systems? Future research on this question is warranted.

My study also showed that innovation knowledge is key for early adopters whereas lack of it can hinder adoption altogether (Chapter 3). This means that although identifying the right intermediaries is important in diffusion processes, there are opportunities for improving the ―nature of communication channels" in the two-step flow diffusion model. Based on my

[15] Type of innovation decision can be three-fold (i.e., optional, collective, and authority). Optional innovation decisions involve one or fewer individuals in making innovation adoption decision. Collective innovation decision require many more persons or organizations to make adoption decisions (i.e., through consensus). Authority innovation-decision occurs by adoption among very few individuals with high positions of power within an organization and forced upon individuals (Rogers 1995).

findings, it is important for change agents (e.g., conservation practitioners) to engage intermediaries with better understanding of the innovation because initial innovation knowledge can be incredibly important during early stages of diffusion processes (Chapter 3). In light of the diffusion of innovations theory, a better way to reinforce the ―extent of change agents' promotion efforts" is by increasing contacts between change agents and potential adopters (Rogers 2003). In the current context, this can be achieved by having more periodic and sustained engagements in order to increase access and transfer of expert knowledge about conservation to the local people.

Nature of diffusion process for complex contagions

One of the main areas of interest in diffusion research is understanding how diffusion processes occur (i.e., nature of diffusion processes) (Rogers 2010). It is well acknowledged that although behaviours and states diffuse through social networks, the nature of social influence or ―contagion effects" can occur in several ways. This analysis is based on a conservation intervention that sought to implement behaviour change in selected fishing villages which in theory would be considered a complex conservation innovation (Mbaru and Barnes 2017) and therefore follow a complex contagion diffusion process (Centola 2018). Adoption trajectories (i.e., diffusion process) suggest that an average of sixteen months might be required before the diffusion process becomes self-sustaining (Fig. A5). There was no direct node-to-node network contagion effect; instead, diffusion processes occurred between network partners in strong cohesive groups (Chapter 3). This finding is in line with earlier studies that argued adoption or diffusion of complex contagions may be conditional on the decisions made by a fraction of peers (Centola & Macy 2007, Valente 1996c). One ‗infected' neighbour appears insufficient to influence adoption or diffusion of complex contagions (Hill et al 2010, Wejnert 2002). Future research on diffusion of complex contagions can devote to analysing how properties of interventions, the nature of communication channels, and extent of change agents' promotion efforts affect their rate of adoption.

Incentives can be counter-productive in diffusion process

In this study, I had instances where some fishers were given the innovation to carry out experimental fishing on a trial basis. As indicated in innovation diffusion theory, this can be considered as offering incentives because the new gear was provided at no cost. Diffusion research has held the view that offering incentives can be a strategy for getting to the critical mass of early adopters who are often needed to accelerate diffusion processes (Valente & Davis 1999). In contrast to this longstanding view, my study showed that people who were provided with escape slot traps either constructed their own escape traps late or did not acquire additional escape slot traps altogether (Chapter 3). In other words, offering subsidies did not necessarily induce an automatic shift towards more sustainable fishing methods. The contribution of my research to the growing body of diffusion literature is apparent by showing that providing incentives may be counterproductive in some diffusion processes such as the one studied here. In the context of conservation, this result may have significant implications to environmental policy makers that aim towards increased subsidies for adoption of fisheries conservation interventions.

Implementation of escape slot traps as a fisheries conservation strategy in Kenya

Several key points of concern regarding the implementation of escape slot trap must be discussed. Firstly, my ecological findings demonstrate that even if escape slot traps are enforced, optimal environmental benefits can only be realized if coupled with gear bans. Indeed, I demonstrated that prohibiting spearguns can effectively double the number of functional entities (i.e., unique combinations of functional traits) affected by fishing (Chapter 6). This means that in order to transform the Kenyan fishery to sustainable levels in the foreseeable future, implementation will have to affect the wellbeing of other subgroups in the system, i.e., speargun fishers. However, speargun are prohibited in Kenya (McClanahan & Mangi 2004). Therefore, by showing how spearguns undermine potential environmental benefits associated with the escape slot trap, my results seem to support existing fisheries regulations that prohibit the use of speargun. This therefore means the pursuit of ecological conservation outcomes associated with escape slot traps can be achieved without the need to pass additional laws that require prohibition of the gears earmarked for removal from the fishery based on my analysis. Instead, enforcing existing laws on gear bans will suffice. However, where a lack of support makes exclusion of spearguns untenable, alternative strategies such as gear exchange programs can be explored in order to minimise the impact on the wellbeing conditions of other members of the fishing community (Chapter 5). These recommendations could be extended to cover other countries given the strong parallels in fishing behaviour in small-scale coral reef fisheries around the globe (McClanahan 2015).

Implementation of many conservation programs requires participation of numerous actors in social-ecological systems (Pannell et al. 2006b; Fisher et al. 2018). By showing that private good can be maximized through public good, there is a need for collective action interventions such as trust, norms of reciprocity, transitivity in networks, monitoring of monitors to improve adoption rates (Finkbeiner et al 2017, Ostrom 1990, Reed et al. 2009). Indeed, the lack of collective action has been cited as a key constraint that can potentially threaten the success of conservation efforts and sustainability processes designed for restoration, biodiversity protection, or poverty alleviation (Finkbeiner et al 2017, Song et al 2018).

Future directions

Throughout my thesis, I have drawn on a number of theories not routinely considered in conservation diffusion research. In doing so, I have challenged a number of long-standing notions on diffusion research but also highlighted the utility of the network approach to conservation diffusion research. As mentioned previously, adoption behaviour is influenced by characteristic of adopters and sometimes the characteristic of the innovation itself. Given the diversity of conservation objectives, future studies that explore a wide range of conservation interventions that integrate characteristics of conservation interventions are warranted.

It is evident that dis-adoption of conservation interventions can occur among people over time. Here, I found a direct positive relationship between material style of life and fishers that abandoned the use of escape slot traps after sometime. My results further showed that higher closeness centrality is a unique characteristic of dis-adopters. In theory, these results indicate that any unfavourable opinion about the conservation practice from dis-adopters could quickly and efficiently spread to other members of the network (Costenbader & Valente 2003, Mbaru & Barnes 2017). Future research that looks into whether dis-adopters can indeed retard or slow down conservation diffusion processes (e.g., rate of adoption) is warranted.

While acknowledging the complexity of social-ecological settings, differences associated with conservation objectives, and diverse landscape of relevant stakeholders, my study proposed a specific criteria for selecting key stakeholders to facilitate distinct conservation objectives. In practice, my guidelines for engagement with the right stakeholders should be ruminated by managers and other conservation practitioners in ways that ensure fair representation of diverse interests, minimize marginalization, and avoid inflaming conflicts between groups. Tracking how my guidelines perform with conservation diffusion processes over time (e.g., the rate of adoption around key players) is thus an exciting avenue for future research.

My longitudinal and multidimensional approach (with controls) complements the guiding principles for evaluating the impacts of conservation interventions on human wellbeing (Woodhouse et al 2015). Findings showed net outcomes associated with the conservation intervention studied varied in terms of magnitude, based on adoption status, across multiple domains of wellbeing over time. This affirms that wellbeing outcomes are dynamic, changing through time or in the course of an intervention (Woodhouse et al 2015). Findings therefore emphasizes the need for future evaluation studies to use multiple indicators in addition to controls and baselines when assessing people‘s wellbeing in evaluation research. Despite my rigorous sampling design, the presence, absence, or adoption of the conservation intervention could not explain all trends observed in this analysis. Future studies that integrate socioeconomic conditions that are related to people‘s wellbeing at the community scale are warranted.

Key findings unveiled in my ecological analysis that added the trait-based approach to standard analyses can provide a concrete foundation for the formulation of the Ecosystem Approach to Fisheries Management in tropical multi-species fisheries. Future research that follows on and further develops the functional approach adopted here is warranted.

Concluding remarks

The success of conservation interventions often depends on the multifaceted and sometimes competing interests and motivations that affect resource use decisions by local people (Beauchamp et al 2018b, Biedenweg & Gross-Camp 2018). Yet despite an extensive literature exploring the effects of conservation on human livelihoods, there is a lack of robust evidence about how conservation should be rolled out, who should be involved, for what role, who benefits, or who loses out. These questions have remained unanswered for decades. Consequently, implementation of conservation continues to suffer poor rates of adoption, even where the need is obvious. In cases where conservation ideas and practices spread, adoption is often random and opportunistic (Weeks et al 2014). The aims of my study were to develop a better understanding on how people adopt conservation innovations (specifically gear-based management), and determine key social and environmental consequences of doing so. Addressing these aims provided some answers to the critical questions highlighted above.

The approaches used to address this aim represent substantial departures from traditional approaches used to study conservation diffusion processes in social-ecological systems. My thesis thus has the capacity to change the way conservation diffusion and consequences of conservation on people and the environment is understood. Despite the current competitive interactions among gear used in the coral reef fishery studied, I found no evidence that escape slot traps did any harm to the local populations affected by intervention. This case study contributes to the growing body of works on impact evaluation of conservation and substantially improves our understanding on the outcomes of fisheries conservation in the context of major change. This analysis also provides wider legitimacy to the paradigm shift from the old era of outright gear prohibition to gear modification as new frontier in gear-based management in fisheries (Condy et al 2015). Finally, I have highlighted substantial discrepancies in the way conservation is currently implemented and how ideally it should. My new framework will not only enable resource manager's better implement conservation but also mitigate the problem of stakeholder identification in conservation diffusion in ways that avoid blueprint approaches and panacea.

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Appendix

Table A1. Summary of RV coefficients including the adjusted and standardized coefficients. Means and variances of the RV coefficient distribution and the p-values are also presented.

		Coefficients					
Sampling period	Site	RV	Adjusted RV	Standardized RV	Mean	Variance	p-value
Time 1 vs Time 2	B	0.51	0.31	4.15	0.12	0	0.01
	C	0.38	0.29	8.27	0.12	0.001	0.001
	D	0.49	0.42	4.02	0.09	0.001	0
	F	0.58	0.44	4.05	0.17	0.001	0.01
Time 1 vs Time 3	B	0.38	-0.26	-2.05	0.12	0	0.01
	C	0.42	0.33	10.01	0.14	0.001	0
	D	0.53	0.37	3.29	0.08	0.002	0.001
	F	0.52	0.29	3.09	0.14	0.001	0.01
Time 2 vs Time 3	B	0.49	0.29	3.27	0.11	0.001	0.01
	C	0.34	0.25	7.33	0.13	0.001	0
	D	0.38	0.23	0.78	0.05	0.001	0.001
	F	0.45	0.37	10.35	0.14	0.001	0.01

Table A2. Exponential random graph model parameter estimates and standard errors. * = parameter estimate is greater than two times the standard error in absolute, indicating that the effect is significant. A positive activity parameter indicate that nodes with the attribute tend to have higher network activity (i.e., more ties) than nodes without the attribute. Interaction parameter denotes homophily for binary attributes. A positive interaction parameter indicate that nodes with attribute tend to have ties with each other. Difference parameter denotes homophily for continuous attributes. A negative difference parameter indicate homophily (i.e., a smaller difference in attribute between the two node is associated with the presence of a tie). T-ratios for the chi-square Goodness of Fit (GOF) were all smaller than 2.0 standard deviation units from the mean.

Effects	Parameter	Standard error	T-ratio
Structural effects (endogenous)			
Edge	-5.23*	0.85	-0.029
Star2	0.04	0.12	0.639
ASA	0.61*	0.29	0.069
ATA	0.76*	0.18	0.041
Actor relation effects (exogenous)			
Agency - Activity	-0.06	0.2	0.622
Agency - Difference	0.17	0.22	0.484
Risk orientation - Activity	0.08	0.09	0.187
Risk orientation - Difference	-0.06	0.16	-0.007
Formal leadership - Activity	0.3*	0.15	0.167
Formal leadership - Interaction	-0.54	1.23	-0.201
Material style of life - Activity	0.2*	0.08	0.326
Material style of life - Difference	0.17	0.17	0.157
Occupational multiplicity - Activity	-0.05	0.12	-0.061
Occupational multiplicity - Difference	-0.05	0.22	0.054
Education - Activity	-0.01	0.03	0.101
Education - Difference	-0.14*	0.06*	-0.104
Innovation knowledge - Activity	0.14*	0.07*	0.319
Innovation knowledge - Difference	-0.3*	0.15	-0.208
Provision of incentives - Activity	-0.24	0.31	-0.271
Provision of incentives - Interaction	0.58*	0.21	-0.302

Key findings of exponential random graph models (ERGMs)

Once accounting for the positive effect of having prior knowledge of the innovation, I show that being active or connected to other actors that are equally active in the network still had a significant positive effect on adoption. In other words, even when network activity and network clustering (i.e., homophily) is taken into account, having knowledge of the innovation still significantly contributed to adoption (Table A2). I found no evidence of homophily or activity effects associated with occupational multiplicity (Table A2). No network effect was collinear with occupational multiplicity either (Table 6). There were homophily effects associated with fishers that were provided with incentives and activity effects associated with opinion leadership and material style of life, however, no network effects were collinear with these attributes (Table A2).

Table A3. Model parameter estimates. Early adopters and late adopters coefficient estimates are based on multinomial logit model whereas dis-adopters are based on RELOGIT model.

Predictors	Early adopters				Late adopters				Dis-adopters		
	B	se	RRR	se(RRR)	B	se	RRR	se(RRR)	B	se	P value
Agency	0.89	0.66	0.42	0.27	-0.21	0.34	1.23	0.42	-19.3	6.14	0.01**
Risk orientation	0.93*	0.42	0.67	0.28	0.39	0.36	1.47	0.53	0.06	7	0.93
Formal leadership	0.06	0.63	1.06	0.66	0.4	0.52	1.49	0.78	-0.6	0.14	0.01**
Material style of life	-0.55	0.47	0.58	0.28	-0.41	0.4	0.67	0.27	0.66	0.32	0.05**
Occupation multiplicity	1.04	0.43	2.82	1.21	0.95**	0.37	0.96	0.36	-0.4	9.88	0.38
Education	-1.26*	0.45	0.78	0.35	-0.14	0.4	0.88	0.35	0.07	2.45	0.56
#Traps	0.25	0.44	1.28	0.57	-0.11	0.38	0.91	0.35	-0.05	0.45	0.34
Innovation knowledge	1.22**	0.43	3.38	1.45	0.66	0.36	1.93	0.69	0.14	1.81	0.69
Age	0.24	0.47	1.27	0.59	0.35	0.42	1.42	0.59	-0.01	0.35	0.84
Provision of incentives	0.58	0.42	1.79	0.75	2.2**	0.39	1	0.39	0.42	3.73	0.42

Log-likelihood: 365.02; Pseudo-R^2: 0.71

Relative risk ratios (RRR) are reported, standard errors (se) of relative risk ratios are reported in parenthesis and are calculated as se(RRR) = exp(β) x se(β). ** p<0.05; * p<0.1.

Table A4. Results of the auto-logistic actor attribute model (ALAAM) for the adopter groups on network attributes. * = parameter estimate is greater than two times the standard error in absolute, indicating that the effect is significant.

Network attribute	**Early adopters**		**Late adopters**		**Non-adopters**	
	Parameter	Standard error	Parameter	Standard error	Parameter	Standard error
Density	-2.06*	0.39	-2.31*	0.92	2.1*	0.87
Popularity	0.52*	0.21	-0.24	0.2	-0.73*	0.21
Direct social influence	-0.17	0.21	0.69	0.44	0.16	0.5
Activity	0.11*	0.05	0.09	0.1	0.1	0.15
Network clustering	0.53*	0.21	0.1	0.15	0.12	0.76
Contagion within groups	1.3*	0.54	0.22	4.2	1.3	2.4
Individual covariate						
Agency			-0.17	0.12	-0.13	0.08
Risk orientation	0.51	0.3			0.84	0.55
Occupation multiplicity			0.36*	0.05	0.58	0.33
Education	-0.07	0.04			0.19	0.14
Innovation knowledge	0.32*	0.15			-0.12*	0.02
Provision of incentives			0.8*	0.23	0.75*	0.18

Table A5. Summary of group level network metrics on graphs for the six villages. T_0, T_1, and T_2 denote network data collected at time one (i.e., baseline surveys), time one (i.e., first follow-up surveys), and time two (i.e., second follow-up surveys) respectively.

Network data	**Village A**			**Village B**			**Village C**			**Village D**			**Village E**			**Village F**		
	T_0	T_1	T_2	T_0	T_1	T_2	T_0	T_1	T_2	T_0	T_1	T_2	T_0	T_1	T_2	T_0	T_1	T_2
# actors	85	84	88	127	152	146	102	113	111	78	85	111	116	73	76	112	82	116
# ties	102	124	96	147	316	200	141	210	161	114	142	161	173	119	118	171	134	186
# unique ties	88	104	90	139	276	176	113	184	133	98	126	133	153	93	102	157	116	170
# duplicated ties	14	20	6	8	40	24	28	26	28	16	16	28	20	26	16	14	18	16
# actors in a connected component	46	76	66	104	152	142	83	113	92	74	85	92	112	67	74	107	77	111
# ties in a connected component	61	118	77	132	316	198	120	210	140	111	142	140	170	112	117	167	130	182
Network diameter	5	9	9	5	7	11	6	7	10	6	5	10	11	8	9	8	10	8
Average geodesic distance	4.15	4.2	4.54	5.55	3.48	5.16	4.33	3.41	4.09	3.95	3.42	4.09	3.89	3.72	3.86	3.82	3.76	3.75
Average path length	2	2	2.1	1.84	1.77	1.93	2.48	2.2	2.7	2.5	2.1	2.2	4.39	4.1	3.9	2.3	2	1.9
Network density	0.03	0.04	0.03	0.02	0.03	0.02	0.03	0.04	0.03	0.04	0.04	0.03	0.03	0.04	0.04	0.03	0.04	0.03
Average clustering coefficient	0.09	0.1	0.04	0.05	0.21	0.1	0.14	0.15	0.16	0.06	0.13	0.16	0.04	0.16	0.07	0.06	0.15	0.09

Table A6. Analysis of all overlaps based on key players identified in each site. C = closeness centrality, B = betweenness centrality, D = degree centrality, E = eigenvector centrality. Expected number of key players = total number of nodes expected to be identified as key players in each site. Observed number of key players = actual number of nodes identified as key players, (+n) denotes number of nodes selected outside respondents list. Respondents selection probability = probability of the key player algorithm to select nodes from the respondents list. Observed % of distinct key players = percentage of non-overlapping nodes. Level 2 = overlaps between two centrality metrics, Level 3 = overlaps between three centrality metrics, Level 4 = overlaps between four centrality metrics.

Description	A	B	C	D	E	F	Overall
Expected number of key players	40	40	40	40	40	40	240
Observed number of key players	40	40+3	40	40+1	40+5	40+4	253
Respondents selection probability	1	0.94	1	0.98	0.89	0.91	0.96
Observed number of overlapping key players	21	25	18	19	18	20	121
Observed % of distinct key players	52.5	62.5	45	47.5	45	50	50.42
Total overlaps	11	14	12	13	13	12	29.66
% overlap	27.5	32.56	30	31.71	28.89	27.3	29.7
Number of distinct key players	19	15	22	21	22	20	119
Overlapping centrality metrics				% overlaps (n)			
E_C	0(0)	7.2(1)	7.2(1)	0(0)	0(0)	7.2(1)	3.6(3)
D_C	0(0)	0(0)	7.2(1)	21.5(3)	0(0)	0(0)	4.8(4)
D_E	7.2(1)	21.5(3)	0(0)	7.2(1)	14.3(2)	0(0)	8.4(7)
D_E_C	7.2(1)	0(0)	0(0)	7.2(1)	0(0)	0(0)	2.4(2)
B_C	28.6(4)	50(7)	7.2(1)	14.3(2)	14.3(2)	21.5(3)	22.7(19)
B_E	0(0)	0(0)	7.2(1)	7.2(1)	7.2(1)	7.2(1)	4.8(4)
B_E_C	0(0)	14.3(2)	0(0)	7.2(1)	14.3(2)	7.2(1)	7.2(6)
B_D	0(0)	0(0)	14.3(2)	0(0)	7.2(1)	0(0)	3.6(3)
B_D_C	21.5(3)	0(0)	7.2(1)	0(0)	0(0)	7.2(1)	6(5)
B_D_E	0(0)	7.2(1)	7.2(1)	14.3(2)	0(0)	21.5(3)	8.4(7)
B_D_E_C	14.3(2)	0(0)	28.6(4)	14.3(2)	35.8(5)	14.3(2)	17.9(15)

Levels of overlap	% overlaps (n)						
Level 2	50(2)	60(3)	62.5(5)	57.1(4)	80(4)	42.9(3)	58.4(21)
Level 3	25(1)	40(2)	25(2)	28.6(2)	0(0)	42.9(3)	27.8(10)
Level 4	25(1)	0(0)	12.5(1)	14.3(1)	20(1)	14.3(1)	13.9(5)

Table A7. Parameter estimates for predictors of keyplayers.

	Closeness			
Covariates	B	Bias	Std. Error	P value
Formal leadership	1.67	0.02	0.42	0.03
Material style of life	-0.01	0.01	0.17	0.98
Education	-0.03	0.01	0.05	0.45
Fishing experience	0.02	0.01	0.02	0.2
Productive assets	1.52	0.02	0.33	0.04
	Betweenness			
Covariates	B	Bias	Std. Error	P value
Formal leadership	1.96	0.02	0.42	0.01
Material style of life	-0.03	0.01	0.16	0.79
Education	0.01	0	0.06	0.87
Fishing experience	0.02	0	0.02	0.14
Productive assets	1.22	0.01	0.83	0.39
	Degree			
Covariates	B	Bias	Std. Error	P value
Formal leadership	1.53	0.01	0.41	0.08
Material style of life	1.21	0.01	0.16	0.07
Education	0.04	0	0.06	0.36
Fishing experience	0.02	0	0.02	0.17
Productive assets	0.11	0.01	0.33	0.67
	Eigenvector			
Covariates	B	Bias	Std. Error	P value
Formal leadership	0.84	0.01	0.44	0.11
Material style of life	-1.22	0.02	0.17	0.07
Education	1.09	0.01	0.06	0.05
Fishing experience	0.02	0	0.02	0.11
Productive assets	1.76	0.01	0.34	0.01

Table A8. Summary statistics (i.e., mean, standard deviation, minimum, maximum, and percent proportions) of control variables included in the regression frameworks. Description of variables as in Table 3.

Variable	Statistic	Control	Adopters	Non-adopters
	N	73 (29.2%)	105 (42%)	72 (28.8%)
Formal leadership	Leaders	8 (11%)	17 (16.2%)	12 (16.7%)
Occupational multiplicity	Minimum	1	0	1
	Maximum	4	4	3
	Mean	2.4±0.8	2.4±0.9	2.3±0.8
Education	Minimum	0	0	0
	Maximum	12	12	12
	Mean	5.6±3.6	4.1±3.7	5.3±3.6
Age	Minimum	18	18	18
	Maximum	75	82	79
	Mean	39±13.7	43±16.3	39±13.2
Fishing dependency	Fishing dependent	70 (95%)	101 (96.2%)	70 (97.2%)
Marital status	Married	66 (90.4%)	93 (88.6%)	66 (91.7%)
Credit access	Credit accessed	64 (87.7%)	90 (85.7%)	61 (84.7%)

Table A9. Summary of results of analyses testing for the differences in baseline values for the different domains of wellbeing between adopters and non-adopters relative to control villages (parallel trends assumption). Material style of life is a score computed from a number of household items as stand-alone attributes for indicators of wealth. Reciprocity captures the number of reciprocated ties based on fishing and information sharing ties. Levels of satisfaction regarding food and income (i.e., subjective livelihood wellbeing), social relationships with other community members (i.e., subjective social cohesion), and work enjoyment and identity (i.e., subjective work wellbeing) are denoted as livWB, cohWB, worWB respectively.

	Kruskal-Wallis ANOVA result			
Wellbeing dimension	Test variable	Mean of rank	H	P - value
Material style of life	Adopter	109.47	10.747	0.005
	Non-adopter	103.38		
	Control	138.68		
Reciprocity	Adopter	115.69	0.804	0.437
	Non-adopter	119.41		
	Control	113.13		
livWB	Adopter	118.02	0.194	0.908
	Non-adopter	114.08		
	Control	114.72		
cohWB	Adopter	114.41	0.371	0.831
	Non-adopter	119.79		
	Control	114.76		
worWB	Adopter	116.98	0.609	0.738
	Non-adopter	119.3		
	Control	111.22		

Table A10. Coefficients of the General linear mixed model Ordinal regression frameworks testing the effect of adoption, non-adoption on wellbeing.

a. Material wellbeing (MSL) - Time 1 (General linear mixed model)

	Estimate	Std. Error	t value
(Intercept)	1.673	0.731	2.288
Controls	-0.141	0.217	-0.651
Non-adopters	-0.097	0.217	-0.449
Formal leadership	0.089	0.255	0.350
Occupational multiplicity	0.148	0.119	1.240
Education	-1.280	0.458	-2.797
Age	-0.005	0.008	-0.632
Fishing dependency	-0.050	0.028	-1.790
Marital status	0.132	0.334	0.395
Credit access	-0.226	0.252	-0.896

b. Material wellbeing (MSL) - Time 2 (General linear mixed model)

	Estimate	Std. Error	t value
(Intercept)	3.173	0.876	3.623
Controls	-0.393	0.249	-1.577
Non-adopters	0.221	0.249	0.888
Formal leadership	0.134	0.294	0.458
Occupational multiplicity	0.134	0.135	0.993
Education	-0.080	0.032	-2.486
Age	-0.024	0.009	-2.801
Fishing dependency	-1.763	0.571	-3.089
Marital status	0.429	0.376	1.140
Credit access	-0.101	0.301	-0.336

c. Subjective livelihoods wellbeing (livWB) - Time 1 (Ordinal regression model)

	Estimate	Std. Error	z value	Pr(>|z|)
Controls	-0.526	0.324	-1.622	0.105
Non-adopters	-0.633	0.300	-2.113	0.035
Formal leadership	-0.145	0.362	-0.402	0.688
Occupational multiplicity	-0.130	0.166	-0.783	0.434
Education	-0.929	0.659	-1.411	0.158
Age	0.007	0.011	0.693	0.488
Fishing dependency	-0.016	0.040	-0.401	0.688
Marital status	-0.561	0.450	-1.247	0.212
Credit access	0.549	0.372	1.475	0.140

d. Subjective livelihoods wellbeing (livWB) - Time 2 (Ordinal regression model)

	Estimate	Std. Error	z value	Pr(>|z|)
Controls	-0.468	0.312	-1.498	0.134
Non-adopters	0.044	0.287	0.155	0.877
Formal leadership	-0.049	0.341	-0.143	0.887
Occupational multiplicity	-0.034	0.160	-0.216	0.829
Education	-0.939	0.681	-1.378	0.168
Age	0.021	0.010	2.132	0.033
Fishing dependency	0.021	0.040	0.525	0.600
Marital status	-1.118	0.423	-2.644	0.008
Credit access	0.293	0.360	0.814	0.415

e. Subjective work enjoyment wellbeing (worWB) - Time 1 (Ordinal regression model)

	Estimate	Std. Error	z value	Pr(>|z|)
Controls	-0.348	0.312	-1.116	0.265
Non-adopters	-0.079	0.293	-0.271	0.786
Formal leadership	-0.214	0.358	-0.599	0.549
Occupational multiplicity	-0.039	0.163	-0.240	0.811
Education	0.366	0.614	0.596	0.551
Age	0.004	0.010	0.410	0.682
Fishing dependency	-0.037	0.038	-0.969	0.332
Marital status	0.236	0.444	0.531	0.596
Credit access	0.430	0.357	1.204	0.228

f. Subjective work enjoyment wellbeing (worWB) - Time 2 (Ordinal regression model)

	Estimate	Std. Error	z value	Pr(>|z|)
Controls	-0.481	0.312	-1.543	0.123
Non-adopters	-0.264	0.283	-0.933	0.351
Formal leadership	-0.311	0.353	-0.881	0.378
Occupational multiplicity	0.225	0.154	1.464	0.143
Education	0.556	0.651	0.854	0.393
Age	-0.006	0.010	-0.580	0.562
Fishing dependency	-0.059	0.039	-1.508	0.132
Marital status	0.081	0.428	0.190	0.849
Credit access	-0.205	0.342	-0.600	0.549

g. Subjective social cohesion (cohWB) - Time 1 (Ordinal regression model)

	Estimate	Std. Error	z value	Pr(>|z|)
Controls	-0.234	0.317	-0.737	0.461
Non-adopters	-0.126	0.300	-0.418	0.676
Formal leadership	-0.016	0.350	-0.047	0.963
Occupational multiplicity	0.054	0.167	0.323	0.747
Education	-0.614	0.634	-0.968	0.333
Age	0.008	0.011	0.786	0.432
Fishing dependency	-0.017	0.040	-0.416	0.678
Marital status	-0.248	0.461	-0.539	0.590
Credit access	0.452	0.366	1.236	0.216

h. Subjective social cohesion (cohWB) - Time 2 (Ordinal regression model)

	Estimate	Std. Error	z value	Pr(>|z|)
Controls	-0.707	0.320	-2.206	0.027
Non-adopters	-0.307	0.302	-1.019	0.308
Formal leadership	-0.582	0.368	-1.582	0.114
Occupational multiplicity	0.195	0.163	1.195	0.232
Education	-1.233	0.689	-1.790	0.074
Age	-0.015	0.010	-1.441	0.150
Fishing dependency	-0.067	0.040	-1.692	0.091
Marital status	0.214	0.463	0.463	0.643
Credit access	-0.272	0.367	-0.739	0.460

i. Relational wellbeing (reciprocity) - Time 1 (General linear mixed model)

	Estimate	Std. Error	t value
(Intercept)	0.611	0.537	1.139
Controls	0.014	0.292	0.047
Non-adopters	0.244	0.154	1.577
Age	0.008	0.005	1.438
Occupational multiplicity	-0.021	0.085	-0.247
Fishing dependency	0.008	0.021	0.406
Formal leadership	-0.021	0.038	-0.546
Education	-0.254	0.325	-0.783
Marital status	-0.473	0.241	-1.960
Credit access	-0.309	0.177	-1.748

j. Relational wellbeing (reciprocity) - Time 2 (General linear mixed model)

	Estimate	Std. Error	t value
(Intercept)	-0.479	0.556	-0.861
Controls	0.280	0.262	1.069
Non-adopters	0.070	0.155	0.453
Formal leadership	-0.007	0.038	-0.181
Occupational multiplicity	0.037	0.085	0.439
Education	0.539	0.354	1.520
Age	0.000	0.005	-0.027
Fishing dependency	0.000	0.021	0.019
Marital status	-0.054	0.233	-0.231
Credit access	-0.210	0.185	-1.136

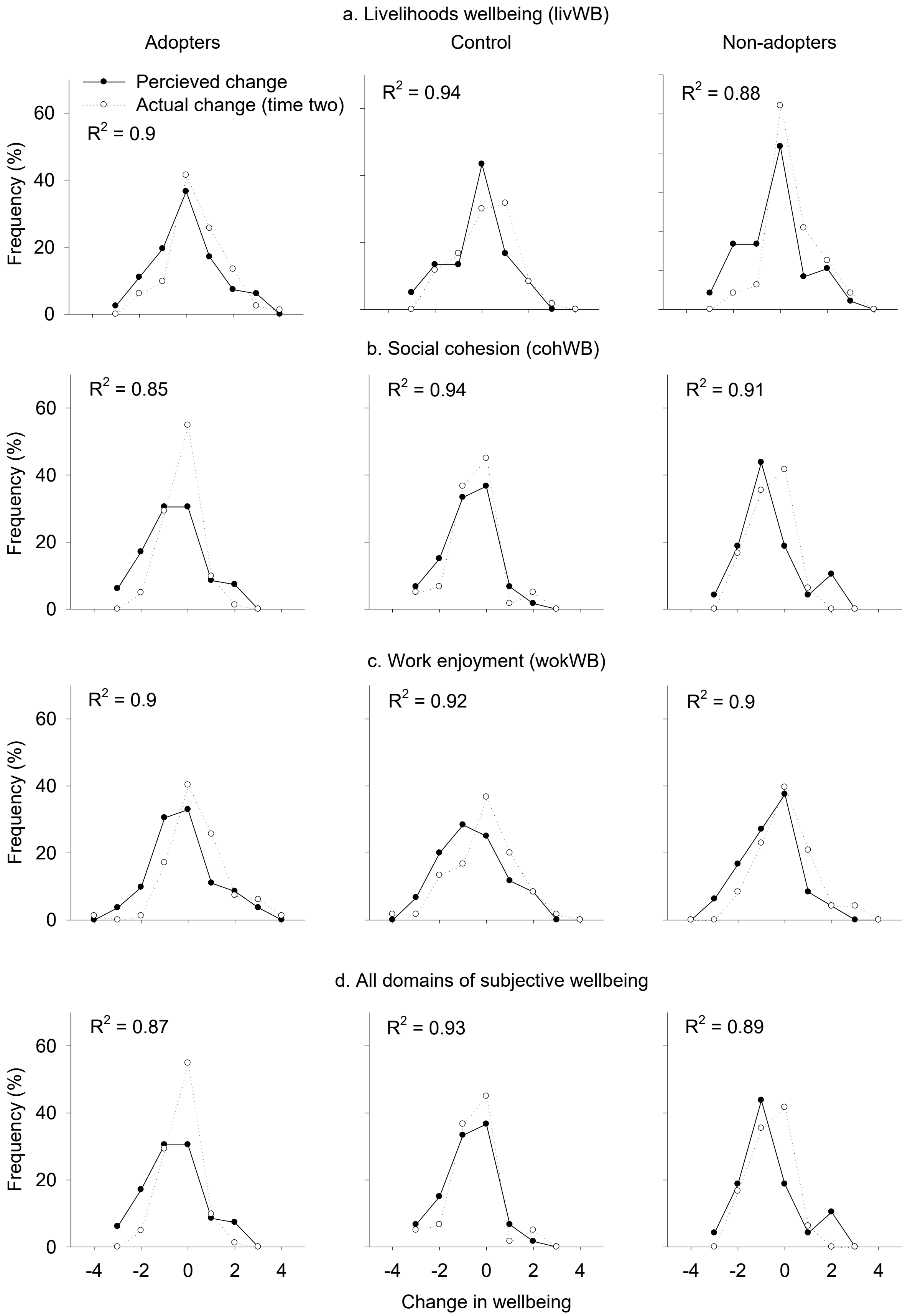
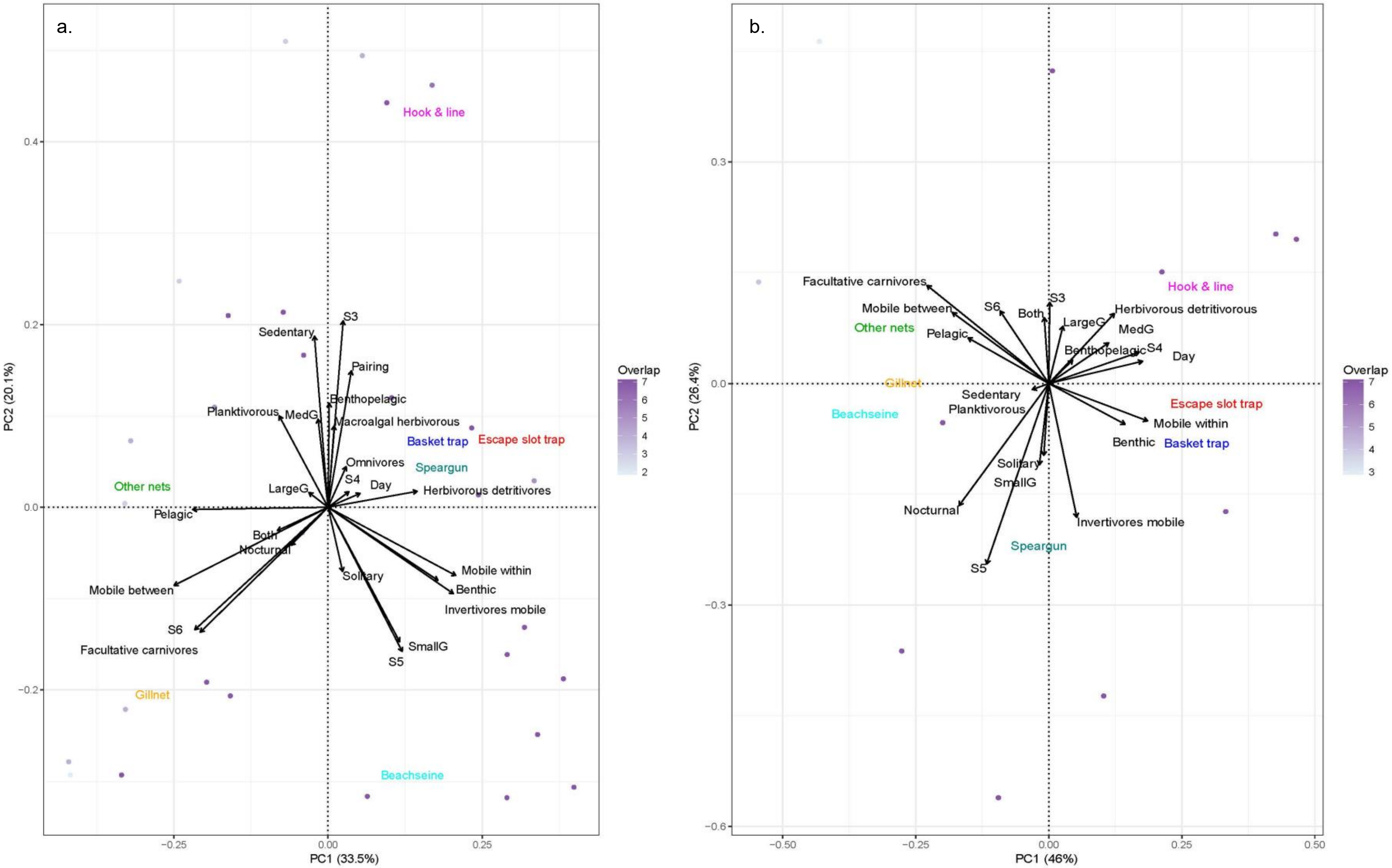
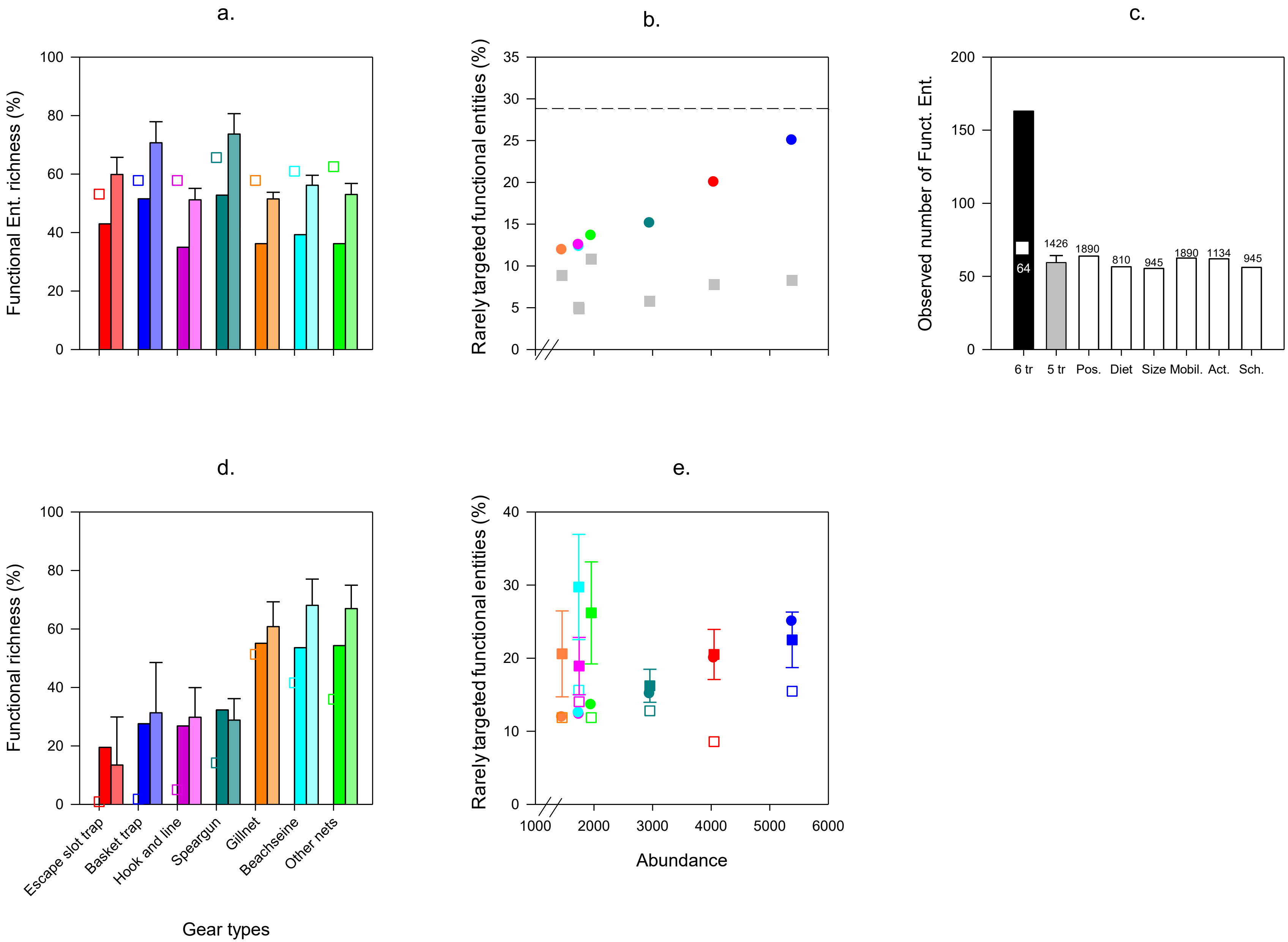


Figure A1. Correlations between actual and perceived change in the three domains of subjective wellbeing.



a.
Hook & line
Sedentary
S3
Pairing
Planktivorous
MedG
Benthopelagic
Macroalgal herbivorous
Basket trap
Escape slot trap
Omnivores
Speargun
S4
Day
Other nets
LargeG
Herbivorous detritivores
Pelagic
Both
Nocturnal
Mobile within
Solitary
Benthic
Mobile between
Invertivores mobile
S6
SmallG
Facultative carnivores
S5
Gillnet
Beachseine
PC1 (33.5%)
PC2 (20.1%)
Overlap
b.
Facultative carnivores
Hook & line
S3
Mobile between
S6
Both
Herbivorous detritivorous
LargeG
Other nets
Pelagic
MedG
Benthopelagic
S4
Day
Gillnet
Sedentary
Planktivorous
Escape slot trap
Beachseine
Mobile within
Benthic
Basket trap
Solitary
SmallG
Nocturnal
Invertivores mobile
Speargun
S5
PC1 (46%)
PC2 (26.4%)
Overlap

Figure A2. Principal component analysis of functional entities contained in (a) 75% (n=29 functional entities) and (b) 50% of catch (n=11 functional entities). Colour gradient represent functional entities shared across a range of gear combinations. Abbreviations used are explained as follows: LargeG (>50 individuals) groups, MedG (20-50 individuals), SmallG (3-20 individuals) indicate size of fish schools. Fish size is coded using six categories: 0-7 cm (S1 – not present in my data), 7.1-15 cm (S2), 15.1-30 cm (S3), 30.1-50 cm (S4), 50.1-80 cm (S5), and >80 cm (S6). Both denotes species active during the day and night.



a.
Functional Ent. richness (%)
b.
Rarely targeted functional entities (%)
c.
Observed number of Funct. Ent.
64
1426
1890
810
945
1890
1134
945
6 tr
5 tr
Pos.
Diet
Size
Mobil.
Act.
Sch.
d.
Functional richness (%)
Escape slot trap
Basket trap
Hook and line
Speargun
Gillnet
Beachseine
Other nets
Gear types
e.
Rarely targeted functional entities (%)
Abundance

Figure A3. Robustness analyses. First, I considered the six possible combinations of five traits out of six. Second, I decreased the number of categories considered for each trait (a crude categorization of functional entities potentially inducing high functional redundancy). For each of these seven changes in trait combinations, I computed the two functional diversity indices presented in the manuscript (i.e. functional richness and rarely targeted functional entities). (a) Functional entities richness in each of the seven gears, expressed as a percentage relative to the total number of functional entities present in all individuals. For each gear, the full-coloured bar shows the richness computed with six traits. The square above each full-coloured bar shows the richness when considering fewer categories per trait. The light-coloured bar on the right of each full-coloured bar shows the mean value (± SD) with five traits only. Colour codes for gears are as in Fig. 10. (b) Rarely targeted functional entities presented as the percentage of individuals that constitute less than 1% of total number of individuals captured in a gear. Horizontal dashed lines symbolize the index values measured on all individuals. (c) Number of functional entities in all individuals captured by all gear. The dark bar on the left shows the pattern observed with six traits. The white square shows the decrease in number of functional entities after reducing the number of categories per trait. The light-gray bar on its right shows the mean value obtained with five traits only (± SD). The six cases with five traits are shown with empty bars on the right with the name of the trait removed at the bottom (Pos, position in the water column; Diet; size; Mobil, mobility; Act, period of activity; Sch, gregariousness). The potential number of functional entities given the number of traits and number of categories in each trait is shown at the top of each bar. (d) Functional richness in each of the seven gears computed as the volume of the functional space filled and expressed as a percentage relative to the functional space filled considering 75% of catch. The coloured empty squares within each full-coloured bar shows the richness when considering fewer categories per trait. The light-coloured bar on the right of each full-coloured bar shows the mean value (± SD) with five traits only. (e) Rarely functional entities (percentage of functional entities with less than 1% of total number of individuals captured in a gear) along the abundance gradient. The values obtained with six traits are represented with coloured points. The values obtained with fewer categories per trait are represented as empty squares. The mean value obtained with five traits (± SD) is symbolized by the coloured squares. Colour codes for gear are as in (a).

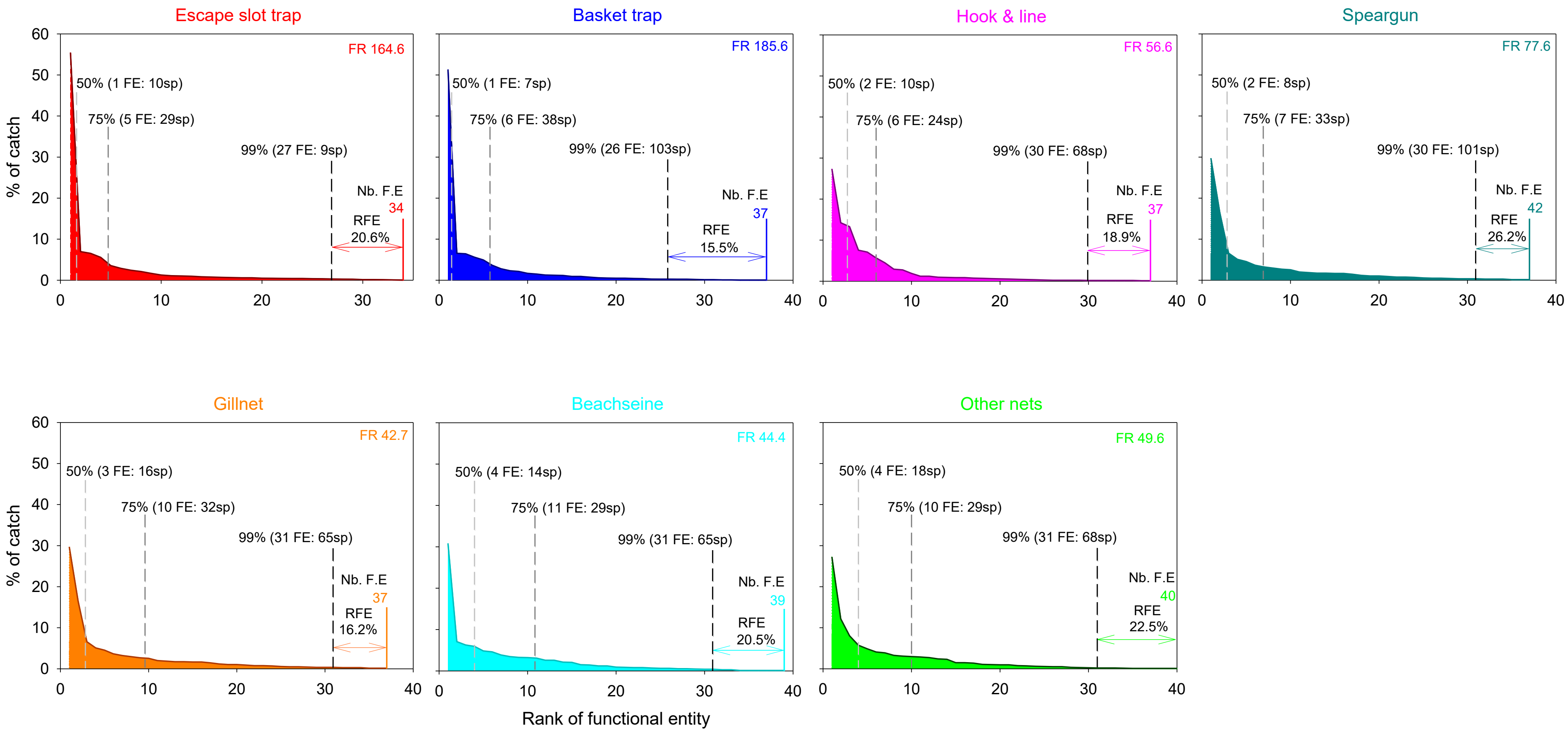

Escape slot trap
FR 164.6
50% (1 FE: 10sp)
75% (5 FE: 29sp)
99% (27 FE: 9sp)
Nb. F.E
34
RFE
20.6%
Basket trap
FR 185.6
50% (1 FE: 7sp)
75% (6 FE: 38sp)
99% (26 FE: 103sp)
Nb. F.E
37
RFE
15.5%
Hook & line
FR 56.6
50% (2 FE: 10sp)
75% (6 FE: 24sp)
99% (30 FE: 68sp)
Nb. F.E
37
RFE
18.9%
Speargun
FR 77.6
50% (2 FE: 8sp)
75% (7 FE: 33sp)
99% (30 FE: 101sp)
Nb. F.E
42
RFE
26.2%
Gillnet
FR 42.7
50% (3 FE: 16sp)
75% (10 FE: 32sp)
99% (31 FE: 65sp)
Nb. F.E
37
RFE
16.2%
Beachseine
FR 44.4
50% (4 FE: 14sp)
75% (11 FE: 29sp)
99% (31 FE: 65sp)
Nb. F.E
39
RFE
20.5%
Other nets
FR 49.6
50% (4 FE: 18sp)
75% (10 FE: 29sp)
99% (31 FE: 68sp)
Nb. F.E
40
RFE
22.5%
% of catch
Rank of functional entity

Figure A4. The distribution of fish individuals into functional entities is displayed for each gear type. The number of functional entities (“Nb F.E.”) present in each gear is shown at the bottom right of the distribution. Functional redundancy (FR) (i.e., mean number of individuals per functional entity) is shown at the top far right corner. The light grey dashed line illustrates number of functional entities contained in 50% of catch. The grey dashed line illustrates number of functional entities contained in 75% of catch while the black dashed line illustrates number of functional entities contained in 99% of catch. Rarely targeted functional entities (RFE) i.e. functional entities contained in 1% of total number of individuals captured in each gear is illustrated in double arrows displayed at far right bottom corner.

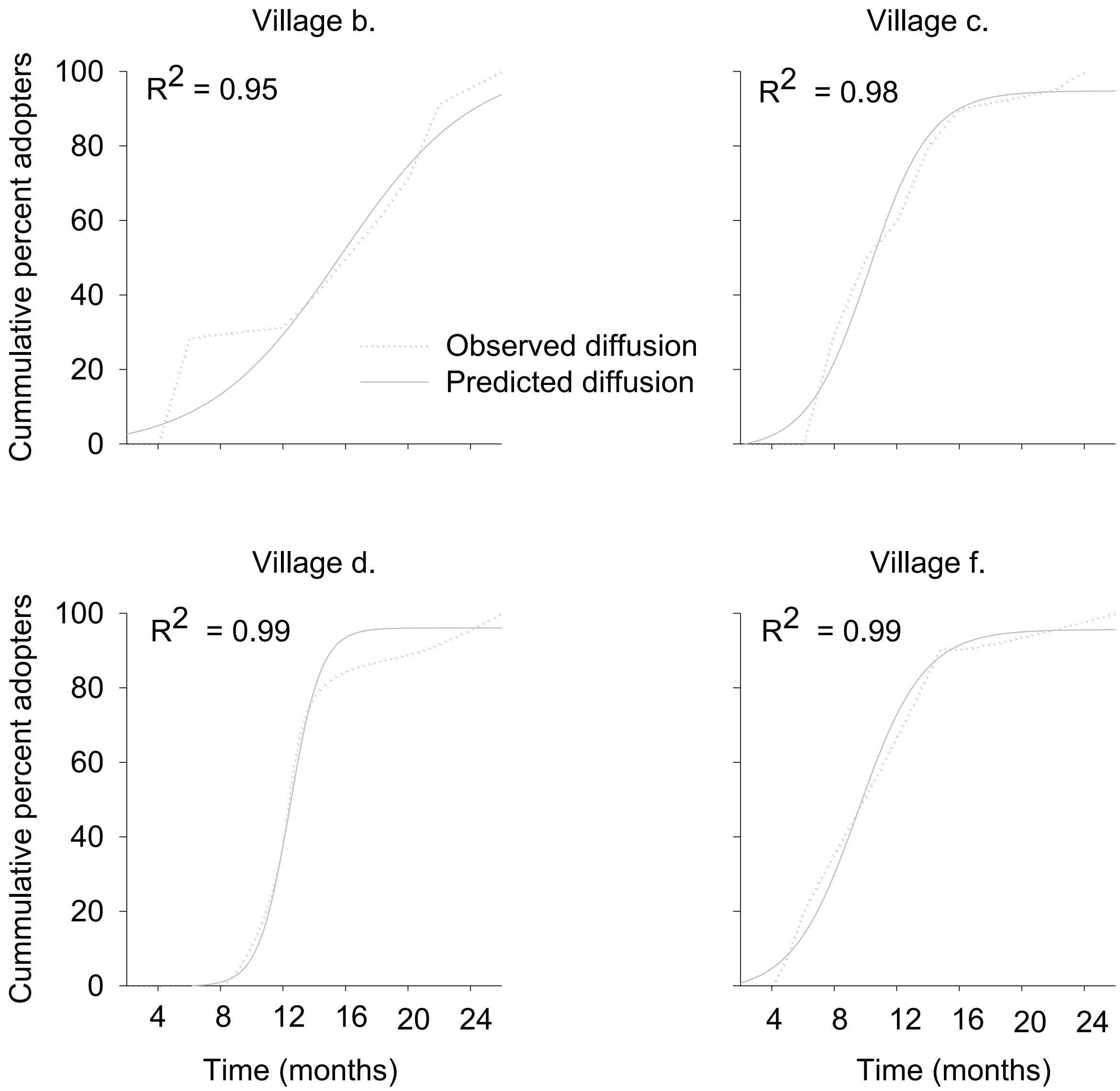


Figure. A5. S-shaped adoption curve of cumulative adopters overtime (black dotted curve). Grey solid curve shows a logistic function describing the diffusion process.