Biological Conservation 210 (2017) 222–232

Contents lists available at ScienceDirect

Biological Conservation

journal homepage: www.elsevier.com/locate/biocon

# Key players in conservation diffusion: Using social network analysis to identify critical injection points

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ARTICLE INFO

*Keywords:*
Conservation
Diffusion
Key players
Social network analysis
Social-ecological systems

ABSTRACT

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 we 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 complex initiatives over a longer time period. Using complete network data among coastal fishers from six villages in Kenya, we apply this approach to select key players for each type of conservation objective. We 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 we identified match the ones typically selected to facilitate conservation diffusion (i.e., 'current players'). Our findings show clear discrepancies between current players and key players, highlighting missed opportunities for progressing more effective conservation diffusion. We 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. These guidelines can also be applied in other research and intervention areas, such as community development studies, participatory research, and community intervention.

## 1. Introduction

Consensus has emerged on the need to involve local stakeholders in development, implementation, and monitoring of conservation initiatives (Leslie 2005, Lundquist & Granek 2005). This involvement can foster long-term interest in conservation, promote local support, and propel the spread of novel conservation ideas and practices (Ostrom 2007, Armitage et al. 2008). 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 (Mertens et al. 2005, Ostrom 2007, Armitage et al. 2008). However, identifying these key individuals (also referred to as 'opinion leaders' or 'change agents') is becoming more complex as the diversity of stakeholders increases and practitioners and policy makers grapple with increasingly variable conservation objectives (Bottrill et al. 2008, Cohen et al. 2012, Arias 2015). These issues are not unique to the conservation setting, indeed, they are prevalent in many research and intervention areas, such as community development studies, participatory research, and community intervention.

To date, managers and practitioners have consistently relied on local community leaders (hereinafter 'leaders') to diffuse and implement conservation actions at the community level (Olsson et al. 2004, Armitage et al. 2008, McClanahan & Cinner 2008). Such approaches have wide appeal because formal leaders are easily identified and leadership characteristics are known to be important for the initiation and maintenance of many initiatives (Pretty 2003, Olsson et al. 2004, Ostrom 2007). Yet while these leaders may truly be better positioned to implement some 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). One explanation for this is that communities are inter-sectoral social arenas with networks of social relations between different actors at various levels (Cohen et al. 2012,

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http://dx.doi.org/10.1016/j.biocon.2017.03.031
Received 22 November 2016; Received in revised form 20 March 2017; Accepted 25 March 2017
0006-3207/ 

Barnes et al. 2017) that are rarely homogeneous; rather, they tend to be 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). Without an understanding of these complex social structures, even relatively simple, low cost conservation initiatives can suffer from poor rates of success (Mertens et al. 2005, Barnes-Mauthe et al. 2015). At worst, they can result in conflicts (Cumming et al. 2006, Cohen et al. 2012, Ban et al. 2013).

In this paper, we draw on social network theory and methods to present guidelines for selecting key players optimally positioned to successfully implement diffusion-related conservation objectives. Social network analysis (SNA) is an analytical approach that can identify social structures 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). We 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, we focus on 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 complex conservation initiatives over a longer time period. We 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 and 4) 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), as discussed in Section 1.1.

Drawing on social network theory, we begin by demonstrating how different conservation information and behaviors associated with the four objectives can be expected to diffuse in a community, and provide guidelines for using SNA to identify key individuals to spearhead these conservation actions. We 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, we 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. We accomplish this by leveraging comprehensive data on social networks and information on conservation diffusion strategies currently being applied along the Kenyan coast.

The Kenyan coast provides a unique case to demonstrate the utility of our approach due to the strong parallels between the local coral reef fishery conservation context and the four conservation objectives described above. With almost 23,000 fishers catching over 16,000 tonnes of fish annually and providing monetary income and animal protein to about 70% of the coastal communities (Glaesel 1997, Tuda et al. 2008), the local fishery grapples with a number of management challenges including an increasing number of small-scale fishers (Ochiewo 2004), and excessive and destructive fishing (McClanahan & Shafir 1990, McClanahan & Obura 1995, McClanahan et al. 2008). To deal with these problems, Kenya has prioritized a number of participatory measures to conserve and manage natural resources. For example, nine marine protected areas (MPAs) have been established, beach management units (BMUs) delegating responsibility of natural resources to local stakeholders have been set up (McClanahan & Mangi 2004), gear-based management approaches that relieve pressure on reproductively immature fish have been implemented (McClanahan & Mangi 2004, McClanahan 2010, Mbaru & McClanahan 2013, Gomes et al. 2014), and 24 Locally Managed Marine Areas (LMMAs) have been established. Although these initiatives have been implemented in a participatory manner, little success has been made in terms of reversing resource depletion and stemming management conflicts (Alidina 2005, Cinner et al. 2012), which calls into question whether greater success might be achieved if stakeholders more optimally placed to facilitate conservation diffusion are involved.

### 1.1. Identifying key stakeholders for specific conservation goals

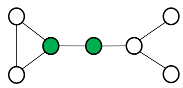
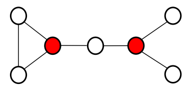
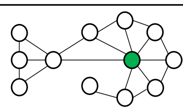
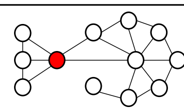
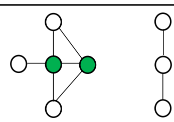
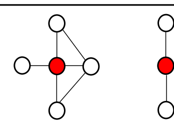
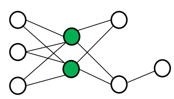
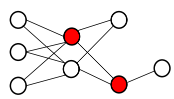
A large body of work in sociology has demonstrated how actors' position in a social network determines how effective they are at acting as a conduit for the spread of information and whether or not they have the power to influence others either directly or indirectly (Freeman 1979, Valente 1996b). Based 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 1979, Valente 1996b). These central positions have often been equated with opinion leadership, change agency, prominence or popularity, all of which are associated with diffusion and adoption behaviors (Valente 1996a, Valente & Davis 1999). There are a range of different centrality metrics which emphasize different structural aspects of complex social systems. We focus on four: (1) closeness centrality (Rochat 2009, Newman 2010), (2) betweenness centrality (Freeman 1979), (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 1). We discuss these measures in turn.

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 (Kapucu 2008, Haddow et al. 2013). *Closeness centrality* 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 (Beauchamp, 1965, 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.

Social-ecological systems are typically comprised of disjointed social structures, so there is often a need to identify brokers who can bridge conservation ideas and practices among disconnected groups (Barnes et al. 2016). *Betweenness centrality* identifies actors who sit between many other actors in a social network (Butts 2008, Stephenson & Zelen, 1989) – 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 (Borgatti et al. 1998, Barnes-Mauthe et al. 2015).

Conservation information or initiatives can sometimes be highly complex, and are not likely to spread as easily from person-to-person as simple information (Wejnert 2002, Hill et al. 2010). In social network theory, 'complex contagions' refer to information or behaviors that a node has to be exposed to through multiple contacts before it

**Table 1**
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 measures.

| Measure | Description | Keyplayer [a] | 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 (Butts 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 1979) | Identifies individuals who would rapidly diffuse complex knowledge and initiatives (Centola & Macy 2007, Valente et al. 2008, Karsai et al. 2014) |
| 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 more complex initiatives in the long term (Butts 2008) |

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

internalizes the information and/or adopts the behaviour (Granovetter 1978, Karsai et al. 2014). *Degree centrality* measures the number of direct ties a node has, and has been positively related to trust (Freeman 1979, Tsai & Ghoshal 1998), influence (Valente et al. 2008), and the spread of complex contagions in social networks (Centola & Macy 2007). The link to complex contagions can be explained by the fact that transitivity and triadic closure are ubiquitous in social networks, which capture the idea that nodes connected to same individual are highly likely to be connected themselves (Rapoport 1953b, Kossinets & Watts 2006, Lou et al. 2013). Thus, individuals with high degree centrality are more likely to influence adoption of complex knowledge and trigger complex contagion cascades because they have multiple direct contacts – many of whom are likely to be connected themselves. Thus, it would only take one node with a low threshold for adoption connected to them to begin the complex contagion process. Degree centrality can therefore identify highly influential nodes with many direct contacts who are more likely to be able to quickly facilitate the spread of complex conservation initiatives or complex knowledge that require multiple direct contacts and persistence for adoption to occur (Granovetter 1973, Centola & Macy 2007, An & Liu 2016). Though we focus on structural effects of transitivity and closure for the transfer of complex knowledge and initiatives, further iterations of this framework could also include measures of tie strength (see Mertens et al. 2005) to capture complex contagions.

Spreading conservation information widely and facilitating widespread adoption of complex conservation initiatives over a longer time period is often necessary to achieve global sustainability outcomes (Pannell et al. 2006, Mace 2014). *Eigenvector centrality* 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 information. Yet because indirect connections are involved, diffusion is more likely to occur over a longer time period, as high eigenvector nodes would first need to influence those directly connected to them before these intermediaries influence others, and so on (Bonacich 1972, Butts 2008). Theoretically, it is argued that spreading actions through intermediaries largely favours simple processes as opposed to complex contagions (Granovetter 1978, Karsai et al. 2014). Yet in part, the measure of eigenvector centrality accounts for nodes with a high level of direct connections, which indicates that these individuals may also be capable of spreading complex contagions (see argument on degree centrality above). In a social-ecological context, eigenvector centrality is therefore likely to be useful for identifying people who can facilitate widespread diffusion of conservation information and complex conservation initiatives over a longer time period through their direct and indirect connections.

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 behaviors (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 (Borgatti 2006, An & Liu 2016). This algorithm incorporates information on centrality measures of interest, but optimally identifies key individuals depending on what they are needed for, while also redressing all computational issues and assumptions associated with each centrality measure (Borgatti 2005, 2006, Borgatti & Everett 2006).

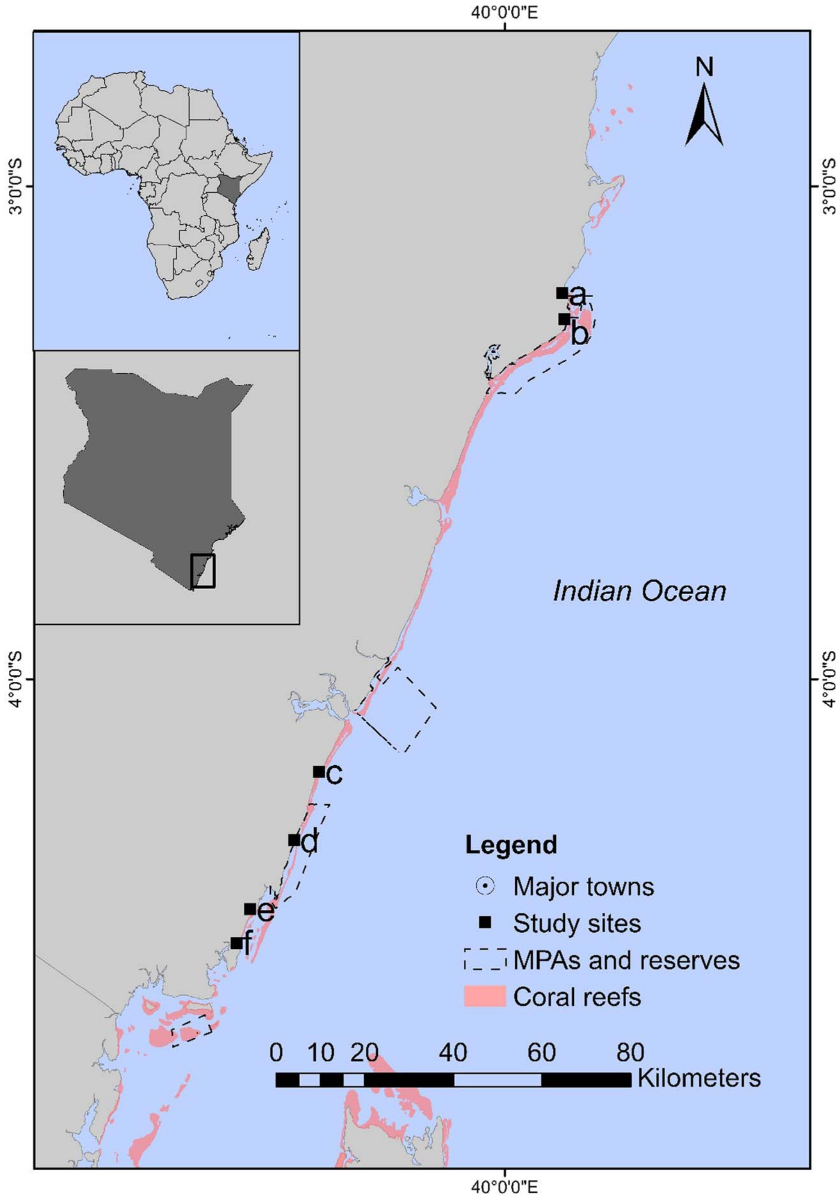



**Fig. 1.** Map showing study sites. Boundaries of Marine Protected Areas (MPAs) and marine reserves are shown as dashed lines.

Table 1 demonstrates graphically how employing the key algorithm builds on centrality metrics but minimizes redundancy (e.g., eigenvector, Table 1) and accounts for separated components (e.g., degree, Table 1) in selecting an optimal set of key players.

## 2. Methods

### 2.1. Data description

Our study sites include six rural fishing villages along the Kenyan coast (Fig. 1), which represent a wide geographic spread and a range of socioeconomic characteristics (Cinner et al. 2009b, Cinner et al. 2010). A high proportion of villagers in our study sites depend on fisheries to support their livelihoods (Cinner et al. 2010). Current conservation initiatives along the Kenyan coast are focused on introducing modifications to basket traps to decrease ecological impacts and increase sustainability of coral reef fisheries (Condy et al. 2014, Gomes et al. 2014). In light of these initiatives, we focused our data collection on study sites where traps represented the dominant fishing gear in use. The target population was therefore defined as active trap 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 238 trap fishers (hereinafter ‘respondents’) were interviewed from November 2015 to February 2016, representing over 95% of the target population at each of the six villages (see Table A3 and A4 for more information on fishing villages). 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. We used recall methods (Marsden 1990, Wasserman & Faust 1994), where each respondent reported his relations. Respondents were also asked to provide basic socioeconomic data. All interviews were done in

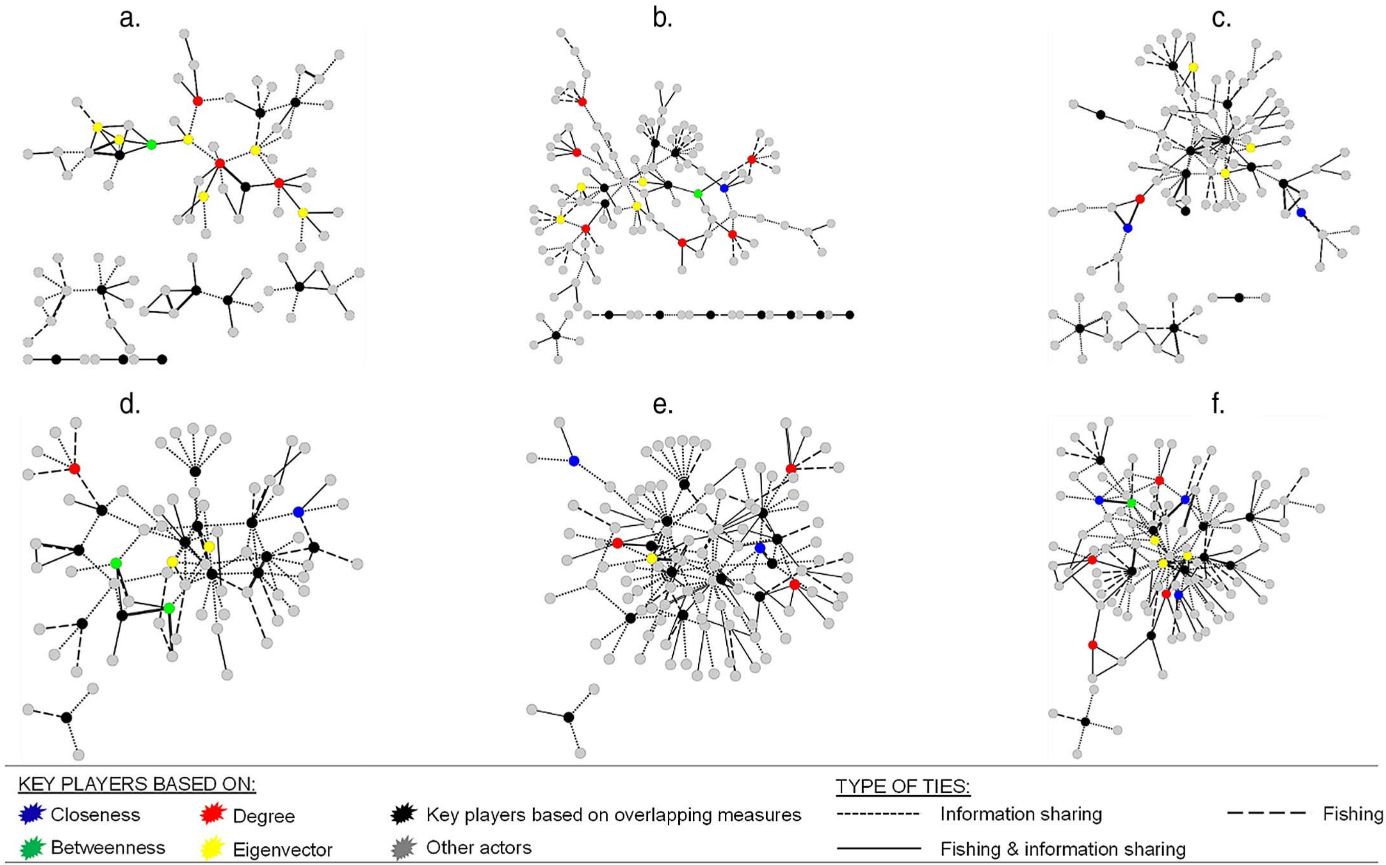



**Fig. 2.** Social network configuration of trap fishers in six Kenyan fishing villages (a, b, c, d, e, f; see Fig. 1). Nodes (representing actors) with the shortest path lengths were placed closest to each other in figurative two-dimensional drawings produced by an algorithm that uses iterative fitting on a force-directed layout (see Supplementary information for network description). Nodes are color coded by their identification as key players based on the four centrality metrics analyzed.

Swahili.

In order to compare the types of individuals we 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), we 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) and specifically asked to indicate the stakeholders they engage with when trying to achieve each diffusion-related conservation objective analyzed here.

### 2.2. 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. 2). We employed a weighted approach (see supplementary information) taking both the number of ties and type of ties into consideration in order to compute the four centrality scores described in the previous section (Newman 2004). Capturing ties using a weighted approach rather than analysing only the presence or absence of one type of tie allows more complex relational states between nodes to be captured (Opsahl et al. 2010). Theoretically, the weight of a tie can be a function of either duration, emotional intensity, intimacy, or exchange of services (Granovetter 1973). Here, we assigned different weights based on the types of tie captured to account for emotional intensity and intimacy, where the weights equalled [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, bringing in new ideas (Watts & Strogatz 1998, Ghasemiesfeh et al. 2013), and for the diffusion of marine and coastal conservation information (Granovetter 1973). However, fishing ties were assigned a higher weight due to their critical role in sharing practical experiences in fishing, which is essential to the diffusion 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).

To identify key players for each conservation objective, we 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, we calculated the harmonic measure rather than the traditional measure because our networks were disconnected (see Fig. 2; Rochat 2009). All centrality metrics were computed on undirected ties. We 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 (Valente 1996a, Rogers 2010). We quantified all overlaps between key players in each site to better understand the relationship between network structure and key players identified for achieving different

**Table 2**
Socioeconomic attributes of all respondents from the six fishing villages ($n = 238$). Formal leaders are fishers elected as leaders of Beach Management Units (BMU), 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.

| | Formal leader n(relative %) | Experience (years) (mean ± SD) | Education (years) (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 |

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), we 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). We 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). We define formal leaders as individuals who are elected as leaders of the Beach Management Unit (BMU) responsible for community-based coastal and marine management in our study sites. In social settings, formal leaders can shape and determine the societal view of a given community (Valente 1996a). 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 is defined as the maximum grade completed in formal education, which 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. Possession of productive assets and MSL are both indicators of wealth and are often associated with social status in a community (Pollnac & Crawford 2000). In computing MSL, we followed Cinner et al. (2009a) by examining a list of 55 items including lighting, transport, household electronics, cooking materials, household structures (such as wall, roof, and floor), among others (see Supplementary Information). A MSL metric was created from the first axis of the PCA (principal component analysis) based on the ownership of the list of household items and structure. Descriptive statistics for all socioeconomic attributes are reported in Table 2. An examination of variance inflation factors indicated there was no signs of multicollinearity among these socioeconomic variables (Fox & Weisberg 2011).

Site was included in our models as a random effect to account for potential differences across sites. To account for issues related to non-independence of the network data, we 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). All model analyses were done in R version 3.3.0 (R Development Core Team 2016).

## 3. Results

### 3.1. Network function and key stakeholders

848 ties used for either fishing, information sharing, or both were reported among our 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. 2). There was some overlap (29.7%, Table A3) 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 were a high number of small components that had no connection to the largest group, and we had greater overlap between key players selected based on the range of centrality scores because of multiple transitive closures, which again is the tendency among two nodes to be connected if they share a mutual neighbour (Rapoport 1953a). Presence of several small components and even isolates (individuals not connected to anyone) ordinarily reduce the average diameter and path length, translating into low clustering coefficients in social networks (Rapoport 1953a, Ghasemiesfeh et al. 2013). Clustering was however 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 SI and Tables A2, A3 for a full summary of network characteristics and overlaps between key players selected for each village).

Our results demonstrate that socioeconomic attributes play an important role in defining key stakeholders well placed to facilitate conservation diffusion in social-ecological systems (Fig. 3). 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. 3, Table A1). When brokerage of conservation actions between disconnected groups is required, which theoretically relates to the foundation of the betweenness centrality measure, our 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

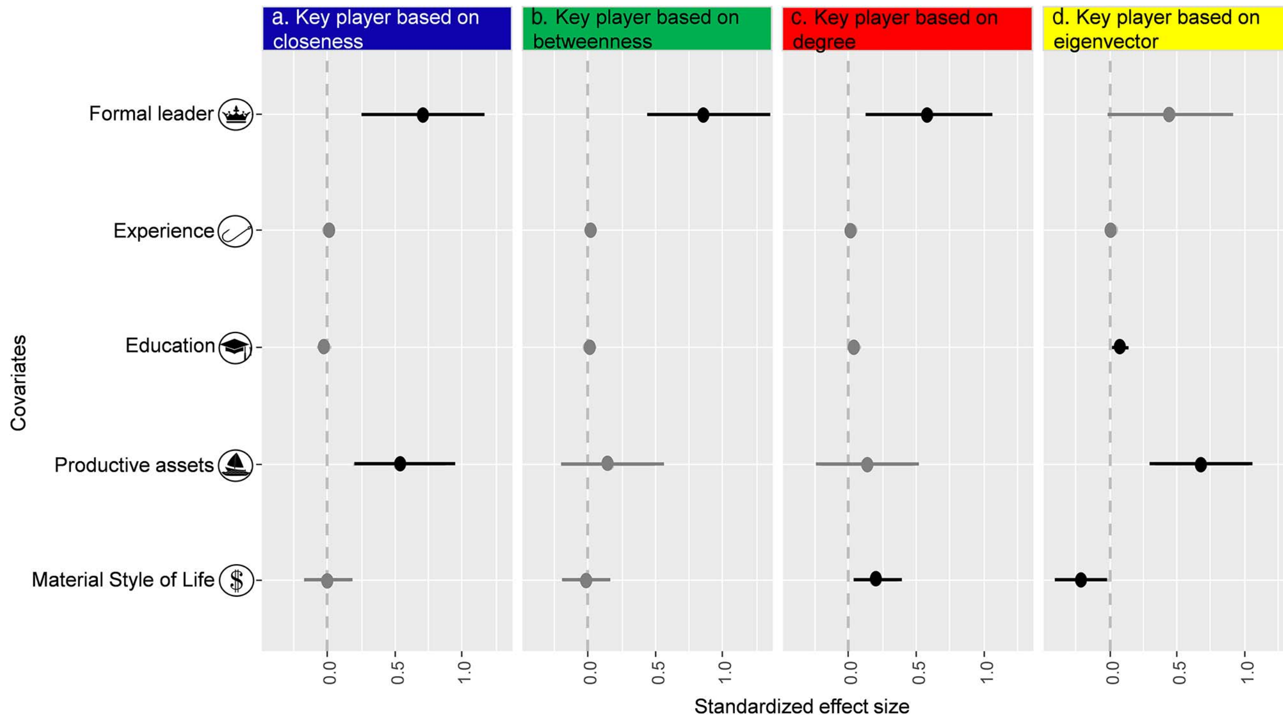



**Fig. 3.** Estimated effect size ( ± 95% confidence intervals) of socioeconomic attributes associated with key players for conservation diffusion based on four different centrality metrics (a–d) using binary logistic regression models.

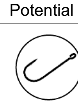
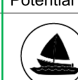
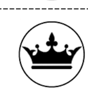
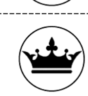
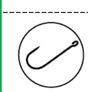
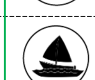
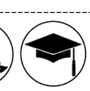
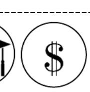
when widespread diffusion of conservation information or long term complex conservation initiatives are needed, which relates to the theoretical foundation of the eigenvector centrality measure.

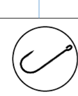
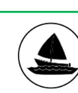
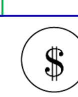
Shown in Table 3, our findings suggest that diverging from the current strategies used to identify key players to achieve conservation diffusion goals could produce more effective results. For instance, we found that conservation practitioners have strong appeal for formal leaders and experienced fishers as key persons needed to spearhead the majority of the conservation objectives we investigated. Yet our 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 3).

## 4. Discussion

Overall, we 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

**Table 3**
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 leaders  Fishing experience  Education  Productive assets  Material style of life 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 3). 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. We discuss the theoretical and practical implications of these results in the following paragraphs before outlining our suggestions for future research.

Firstly, our 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 (Nunan 2006, Bodin & Crona 2008, Cohen et al. 2012). In Kenya for example, fishing behaviour displays evidence of territoriality among groups, and management of marine natural resources is primarily coordinated through BMUs (Oluoch & Obura 2008, Cinner et al. 2009c). These decentralized community-based management organizations allow multi-stakeholder participation in natural resource management (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 resource system (managers) and the clients system (local communities). 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 our 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 (Edmondson 2003, Balkundi & Kilduff 2006, Dearing et al. 2006, Bodin & Crona 2008). This is partially supported by our results showing that formal leadership is not important for predicting key players ideally placed to facilitate widespread diffusion (Fig. 3). 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 (Ascroft & Agunga 1994, 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, our results also suggest that the importance of formal leadership for conservation diffusion likely 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, Kenya is known to be a highly centralized and hierarchical society, which is reflected in fisher's social networks, and our study sites had minimal ethnic differences and low levels of migration behaviour (Table A4). These societal differences may partly explain our contrasting results.

Depending on the social structure and the conservation objective at hand, our 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, our results show that experience is not significantly related to identifying key players for this objective (Table 3). 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 behaviour 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 practice 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 (Valente & Davis 1999, Conley & Moote 2003). Perhaps more importantly, excluding these stakeholders may have inhibiting effects on adoption and diffusion of more complex conservation innovations (Nabseth & Ray 1974, Bongaarts 1994). 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).

Our 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 (Platteau 2004, Mertens et al. 2005, 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, we recognize and highlight the importance of MSL – a measure of wealth – in selecting key players in the conservation process. In fact, we 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.

Our results also show that non-elites should be brought on board for widespread impact of conservation initiatives 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 (Kjelson & Johnson 1978, Deudero et al. 1999, Brewer et al. 2006, 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 and promote equity in 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.

## 5. Conclusion

Here we 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, we 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, our 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. The proposed approach also has substantial relevance for broader research and intervention areas, such as community development studies, participatory research, and community intervention. Tracking how our guidelines perform with diffusion processes over time in these areas is thus an exciting avenue for future research. In practice, our guidelines for engagement with the right stakeholders should be ruminated by managers and other practitioners in ways that ensure fair representation of diverse interests, minimize marginalization, and avoid inflaming conflicts between groups.

## Acknowledgments

This work was supported by a Marine Science Management (MASMA) grant provided by the Western Indian Ocean Marine Science Association (WIOMSA) (MASMA/OP/2014/04). Thanks are extended to the Wildlife Conservation Society (WCS) for coordinating this research through Dr. Nyawira Muthiga and Dr. Tim McClanahan. Joshua Cinner provided suggestions and comments on earlier drafts. We are indebted to our field research assistants Stephen Wanyonyi, Innocent Mulwodo, and all BMU leaders for their support in the field. This work was supported by the Western Indian Ocean Marine Science Association's (WIOMSA) Marine Science for Management (MASMA) program. M.B. was supported by NSF Social, Behavioural, and Economic Sciences Postdoctoral Fellowship Grant #1513354. The funders played no role in the collection, analysis, and interpretation of data or in the writing of the report. We have no conflict of interest to declare.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/10.1016/j.biocon.2017.03.031.

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