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Untangling the drivers of community cohesion in small-scale fisheries

Steven M. Alexander

National Socio-Environmental Synthesis Center, University of Maryland, USA; Stockholm Resilience Centre, Stockholm University, Sweden stevealexander11@gmail.com

Örjan Bodin Stockholm Resilience Centre, Stockholm University, Sweden orjan.bodin@su.se

Michele L. Barnes James Cook University, ARC Centre of Excellence for Coral Reef Studies, Australia; University of Hawaii at Manoa, Department of Botany, USA michele.barnes@jcu.edu.au

Abstract: Sustainable fisheries require strong management and effective governance. However, small-scale fisheries (SSF) often lack formal institutions, leaving management in the hands of local users in the form of various governance approaches (e.g. local, traditional, or co-management). The effectiveness of these approaches inherently relies upon some level of cohesion among resource users to facilitate agreement on common policies and practices regarding common pool fishery resources. Understanding the factors driving the formation and maintenance of community cohesion in SSF is therefore critical if we are to devise more effective participatory governance approaches and encourage and empower decentralized, localized, and community-based resource management approaches. Here, we adopt a social relational network perspective to propose a suite of hypothesized drivers that lead to the establishment of social ties among fishers that build the foundation for community cohesion. We then draw on detailed data from Jamaica's small-scale fishery to empirically test these drivers by employing a set of nested exponential random graph models (ERGMs) based on specific structural building blocks (i.e. network configurations) theorized to influence the establishment of social ties. Our results demonstrate that multiple drivers are at play, but that collectively, gear-based homophily, geographic proximity, and leadership play particularly important roles. We discuss the extent to which these drivers help explain previous experiences, as well as their implications for future and sustained collective action in SSF in Jamaica and elsewhere.

Keywords: cooperation, ERGM, fisheries governance, fisheries management, social capital, social network analysis

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I. Introduction

Sustainable fisheries require strong management and effective governance (Bundy et al. 2017). Yet small-scale fisheries (SSF) often lack formal institutional capacity, which hampers effective governance (Andrew et al. 2007; Salas et al. 2007; Barnes-Mauthe et al. 2013b). Management is thus often left in the hands of local users in the form of various governance approaches (e.g. local, traditional, or comanagement) (Pomeroy 1995; Cinner et al. 2012; Wamukota et al. 2012). The effectiveness of these approaches inherently relies upon some level of cohesion among resource users in order for all or the majority of actors to get together to devise, implement, and maintain policies and practices regarding common pool fishery resources (Pomeroy and Andrew 2011; Cinner et al. 2012).

Broadly stated, social cohesion refers to the forces that hold individuals and communities together through the maintenance of social relationships (Moreno and Jennings 1938; Festinger et al. 1950; McPherson and Smith-Lovin 2002). Social cohesion contributes to the development of shared views, perceptions, behaviors, and norms (Friedkin 2004; Prell et al. 2010), all of which are particularly important in bringing communities together to collectively manage SSF where institutional capacity is weak and formal authorities are absent. In this context, community cohesion (i.e. social cohesion within a community) can reduce transaction costs, facilitate the development of commonly agreed upon harvesting rules, and contribute to self-monitoring (Pretty 2003; Berkes 2010; Nunan et al. 2015).

Even where SSF have some institutional capacity, community cohesion can play an important support role. For example, community cohesion can facilitate social learning and contribute to navigating and responding to larger-scale institutional or environmental change (e.g. the establishment of MPAs, changes in user rights, climate-induced shocks) (Ostrom 1990; White et al. 2002; Christie 2004; Salas and Gaertner 2004; Mills et al. 2013; Stevens et al. 2015; Barnes et al. 2017b; Crona et al. 2017). In addition, repeated social interactions between individuals can lead to the development of trust and contribute to the establishment of mutual understanding about the status and conditions of natural resources (Ostrom 1990, 2005; Ostrom and Walker 2003).

Despite the importance of community cohesion for supporting effective governance of SSF, we know little about the factors that bring and hold communities together in this context (Jentoft 2000; Kumar 2005; Cinner et al. 2012; Nunan et al. 2015). Developing an understanding of these factors is critical for several reasons. First, we need to understand how communities of resource users emerge and develop if we are to devise more effective participatory governance approaches. This understanding is also critical for devising policies aiming to encourage and empower decentralized, localized, and communitybased resource management approaches - i.e. the devolution of rights from public authorities to local communities (Pomeroy et al. 2004; Carlsson and Berkes 2005). Second, community cohesion forms an important foundation for the emergence and maintenance of key social processes that support effective resource governance (e.g. collective action, coordination, and learning; see Friedkin 1998; Bodin and Crona 2009; Frank 2011; Barnes et al. 2016). Though community cohesion has been studied in other contexts such as schools, sports teams, economic development, and civic engagement (e.g. Onyx and Bullen 2000; Narayan and Cassidy 2001; Krishna 2002; Friedkin 2004), recent research has demonstrated that well-studied social-structural or social network theories do not always seamlessly apply to common-pool resource settings (Crona et al. 2017). For example, Barnes et al. (2017a) showed that positive effects of brokerage (ties that bring disparate groups together), which have been well-studied in the economic and organizational sciences (e.g. Burt 2004), did not appear to manifest for Hawaii's longline fishers.

In this paper, we adopt a social relational network perspective (*sensu* Bodin and Crona 2009; Alexander and Armitage 2015) to propose a suite of hypothesized drivers that lead to the establishment and maintenance of social ties among fishers, which build the necessary foundation for community cohesion. We then draw on detailed data from Jamaica's small-scale fishery to test these hypotheses empirically. Specifically, we develop and analyze a suite of empirically driven and nested exponential random graph models (ERGMs) based on specific structural building blocks (i.e. network configurations), (see, e.g. Davis and Leinhardt 1972) theorized to capture different drivers (i.e. processes) in which social ties are established. We then discuss the extent to which these drivers help to explain previous experiences (e.g. Crona and Bodin 2006; Barnes-Mauthe et al. 2013a, Cox et al. 2016), as well as their implications for future and sustained collective action with regards to SSF in Jamaica and elsewhere.

2. Drivers of social tie formation in small-scale fisheries

There are three broad drivers frequently identified in the sociological literature that are thought to contribute to the establishment of social ties and understanding how patterns of ties – i.e. *social networks* – evolve over time. These drivers include: (1) structurally driven tie formation; (2) attribute driven tie formation; and (3) exogenous contextual factors (Table 1). Structurally driven mechanisms posit that the establishment and maintenance of social ties are driven by existing direct and indirect connections (Rivera et al. 2010; Lusher et al. 2012). Attribute driven mechanisms posit that the establishment and maintenance of actors (Rivera et al. 2010; Lusher et al. 2012). Exogenous contextual factors suggest cultural, social, geographic, and/or ecological environments of individual actors drive the establishment and maintenance of social ties.

While significant streams of research on these mechanisms have emerged, they have often done so in isolation (Rivera et al. 2010), and several scholars have called for an approach that considers multiple drivers of tie formation simultaneously (Monge and Contractor 2003; Rivera et al. 2010; Henry et al. 2011; Lusher et al. 2012). Accordingly, we focus here on understanding the role and interplay of four different processes spanning these drivers. The first driver is the structurally driven tie formation process of *triadic closure* – i.e. the general tendency for friends of a friend to be friends (Granovetter 1973) - (e.g. Ramirez-Sanchez and Pinkerton 2009). The second driver is the attribute driven process of homophily - i.e. the formation of social ties between individuals who share some commonality such as fishing gear type – (e.g. Barnes-Mauthe et al. 2013a). The third driver represents the exogenous contextual factor geographic proximity - i.e. the formation of social ties between individuals who regularly occupy similar geographic spaces – (e.g. St. Martin and Hall-Arber 2008). The fourth driver is an additional attribute driven process found to be critical in SSFs and other CPR contexts: leadership (e.g. Alexander et al. 2015; Crona et al. 2017).

The four processes and associated hypotheses examined here were selected through a stepwise process. The three broad categories identified by Rivera et al. (2010) and Lusher et al. (2012), which have been distilled from theoretical and empirical studies, serve as the starting point. For each broad category we then turned to the small-scale fisheries literature for empirical examples (including both qualitative studies and social network analysis). Simultaneously, we turned to the empirical context of this study to identify other relevant processes (e.g. leadership, landing sites). We then use the empirical setting as a final filter to identify those most relevant to examine in this context – e.g. while ethnicity and kinship have been identified in the small-scale fishery literature they are not appropriate for this context. Accordingly, this is not an exhaustive list of relevant hypotheses in relation to what factors and mechanisms might be contributing to community cohesions. Theoretical and empirical work informing each of the four hypotheses is included below.

 Structurally Establishment and maintenance driven by of social ties are driven by of social ties are driven by existing direct and indirect commer social ties will tend to existing direct and indirect actine direct commer social ties are at 2010; Lusher et al. 2010; Lusher et al. 2012) Attribute Establishment and maintenance driven by effriends with the friends of their friends (Granovetter 1973) Attribute Establishment and maintenance homophily – i.e. tie formation of social ties are driven by similarities (or differences) in the attributes of actors (Rivera et al. 2012) Attribute Establishment and maintenance homophily – i.e. tie formation of social ties are driven by some commonality (e.g. age, gender, education, etc.) (McPherson et al. 2010; Lusher et al. 2012) Certain attributes can make particular actors more/less sought after, for example being a state actor during decision-making processes in developing new policies (Ingold and Fischer 2014). Exogenous Cultural, social, geographic, and/or ecological environments of individual actors drive the sharing network and a resource of individual actors drive the sharing network and a resource of individual actors drive the sharing network and a resource or contextual 	 Preferential attachment – those who have more social ties will tend to accrue additional ties more rapidly (Barabási and Albert 1999) Triadic closure – i.e. one is likely to be friends with the friends of their friends (Granovetter 1973) Homophily – i.e. tie formation between two individuals who share some commonality (e.g. age, gender, education, etc.) (McPherson et al. 2001). Certain attributes can make particular actors more/less sought after, for example being a state actor 	 Triadic closure is one way to capture bonding ties – which have been repeatedly noted as important in SSF (e.g. Ramirez-Sanchez and Pinkerton 2009; Alexander et al. 2015) Gear based homophily (Crona and Bodin 2006; Cox et al. 2016) Kinship based homophily (Ramirez- 	Triadic Closure Gear based
Attribute Establishment and maintenance Homophily - i.e. (if formation driven* of social ties are driven by between two individuals who share similarities (or differences) in between two individuals who share similarities (or differences) in between two individuals who share similarities (or differences) in between two individuals who share the attributes of actors (Rivera education, etc.) (McPherson et al. et al. 2010; Lusher et al. 2012) 2001). certain attributes can make particular actors more/less sought after, for example being a state actor during decision-making processes in developing new policies (Ingold and Fischer 2014). Exogenous Cultural, social, geographic, Involvement in other types of social factors of individual actors drive the sharing networks (e.g. an information	 Ince Homophily – i.e. tie formation between two individuals who share some commonality (e.g. age, gender, education, etc.) (McPherson et al. 2001). Certain attributes can make particular actors more/less sought after, for example being a state actor 	 Gear based homophily (Crona and Bodin 2006; Cox et al. 2016) Kinship based homophily (Ramirez- 	Gear based
Exogenous Cultural, social, geographic, • Involvement in other types of social Ir contextual and/or ecological environments networks (e.g. an information methods factors of individual actors drive the sharing network and a resource •	during decision-making processes in developing new policies (Ingold and	Sanchez 2011)* • Ethnic based homophily (e.g. Barnes- Mauthe et al. 2013a)* • Leaders as individuals being sought after (e.g. Alexander et al. 2015; Crona et al. 2017)	homophily Leaders/wardens
 establishment and maintenance sharing network) (Lusher et al. 2012) G of social ties Geography and space brings and holds people together (Rivera et al. 2010; Lusher et al. 2012) 	 Fischer 2014). Involvement in other types of social ents networks (e.g. an information e sharing network and a resource sharing network) (Lusher et al. 2012) Geography and space brings and holds people together (Rivera et al. 2010; Lusher et al. 2010; Lusher et al. 2010) 	Involvement in other types of social networks • Co-op membership [†] Geographic Proximity • Fishing grounds (e.g. Maya-Jariego et al. 2016)* • Landing sites (no empirical work to date)	• Geographic Proximity

Table 1: Drivers of social tie formation with select examples.

Hypothesis 1. *Triadic closure contributes to the formation of social ties among small-scale fishers.*

Triadic closure and clustering are known to be some of the most common structurally driven tie formation mechanisms in social networks (Lusher et al. 2012). They have been observed in a diversity of contexts ranging from a neighborhood church and textile factory to digital communications at a large university (Hammer 1980; Kossinets and Watts 2006). These dense structures can be seen as a network representation of bonding social capital (see, e.g. Berardo 2014). Social capital has been of particular interest to those studying SSF (e.g. Ramirez-Sanchez and Pinkerton 2009; Barnes-Mauthe et al. 2015) because it has repeatedly been linked to successful natural resource management outcomes (Ostrom 1990; Pretty 2003), particularly the management of common pool fishery resources (Gutiérrez et al. 2011; Cinner et al. 2012). Bonding social capital is characterized by strong, localized social ties and high levels of social cohesion (Narayan and Cassidy 2001; Woolcock 2001). As such, it can be particularly important in SSF where institutional capacity is weak because it can reduce transaction costs, contribute to the development of trust and commonly agreed upon harvesting rules, and promote self-monitoring (Pretty 2003; Berkes 2010; Nunan et al. 2015).

Hypothesis 2. Gear-based homophily contributes to the formation of social ties among small-scale fishers.

Homophily is one of the most ubiquitous drivers of social tie formation (McPherson et al. 2001). Accordingly, the presence and role of homophily has been documented in several common pool resource use settings, including marine fisheries (Crona and Bodin 2006; Barnes-Mauthe et al. 2013a; Cox et al. 2016). The implications of this are substantial as the resulting network structures dictate the information people receive and the attitudes, beliefs, and values they are exposed to (Friedkin 1998; Frank 2011; Frank et al. 2011; Barnes et al. 2016). While homophily structures all types of network ties (e.g. marriage, friendship) and can be attributed to many socio-demographic characteristics (e.g. age, gender), here we focus on homophily based upon the choice of fishing gear (hereafter referred to as gearbased homophily). Being successful as a small-scale fisher, in an environment that is incredibly heterogeneous and highly variable, requires specific and contextual information (Crona and Bodin 2006). Therefore, it is likely that fishers will seek and share information with others whose experiences and resource needs are similar. Thus, in instances where a SSF is characterized by multiple gear types, which is incredibly common throughout the globe (Salas et al. 2007, McClanahan and Cinner 2008), sharing information with others using similar gears is likely. Indeed, gear-based homophily has been documented in SSF including coastal Kenya (Crona and Bodin 2006) and the Dominican Republic (Cox et al. 2016).

Hypothesis 3a. Geographic proximity, here captured by any two fishermen sharing a landing site, contributes to the formation of social ties among small-scale fishers.

Hypothesis 3b. Geographic proximity, via a shared landing site, drives smallscale fishers to avoid establishing social ties with each other due to direct competition over nearby marine resources.

Geographic proximity – i.e. the formation of social ties between individuals who regularly occupy similar geographic spaces – is another driver of social tie formation found to be common across several settings (Gieryn 2000; Rivera et al. 2010; Lusher et al. 2012; Maciejewski and Cumming 2015). In the context of near-shore SSF, landing sites reflect geographic proximity and serve as social spaces where fishers are more likely to have repeated interactions with others on their way to go fishing or upon their return. Accordingly, landing sites serve as a likely mechanism driving the establishment and maintenance of social ties (hypothesis 3a).

However, we also acknowledge that competition between fishers at the same landing sites can be fierce since they often go to the same/overlapping fishing sites and fish for common target species (Basurto et al. 2016). Thus, the incentive for collaboration might be negative. In such cases, one would expect that sharing a landing site would instead imply a propensity of fishers to avoid establishing social ties between each other. Therefore we suggest an alternative hypothesis (3b), noting however that these hypotheses and associated processes are not mutually exclusive, i.e. a positive and negative effect of geographic proximity on the establishment of social ties may exist simultaneously.

Hypothesis 4. Key leaders within communities drive the establishment and maintenance of social ties among small-scale fishers.

The presence of local community leaders – e.g. president of a fisher cooperative – serves as another driver of social tie formation. Many leaders will be sought after for specific information related to their position, experience, and knowledge. This leads to community leaders having more ties on average (Alexander et al. 2015; Mbaru and Barnes 2017). In the context of SSF, leadership has been noted as a key attribute for success (Grafton 2005; Bodin and Crona 2008; Gutiérrez et al. 2011; Alexander et al. 2015; Crona et al. 2017). Furthermore, as Crona et al. (2017) note, leaders can act as hubs, bringing people together, playing an important role in supporting and activating community cohesion.

3. Testing the drivers empirically

3.1. Methodological approach

Our empirical example uses detailed data on small-scale fishers operating within, or in close proximity to the Bluefields Bay *Special Fishery Conservation Area* (SFCA) in Jamaica (Figure 1). Jamaica has an active small-scale and artisanal fishery (Aiken and Kong 2000) that can be characterized as mixed gear (e.g. fish traps, gill nets, handlines, spear guns) and multispecies (e.g. reef fish, spiny lobster, conch, small coastal pelagic finfish, large offshore pelagic finfish). The fisheries are largely reef-dependent, occur near shore (Aiken and Kong 2000),

and contribute to the livelihoods of 75% of households in some communities and nearly 5% of the island's entire population (Burke and Kushner 2011; Burke et al. 2011). Moreover, they provide close to 10% of protein consumed by Jamaicans, making the health of coral reefs a matter of food security, especially for rural fishing communities (Waite et al. 2011). In an effort to protect near-shore fisheries and other marine and coastal resources, Jamaica has established 14 SFCAs – i.e. marine no-take areas – which range in size from 1 to 18.73 km² and have a legal mandate for co-management.

The Bluefields Bay SFCA is located along the southwest coast of Jamaica in the parish of Westmorland and is 13.59 km² – making it among the largest in Jamaica (Figure 1). Officially legislated and declared in 2009, a Memorandum of Agreement (MoA) was established with the Bluefields Bay Fishermen's Friendly Society (BBFFS). Today, Bluefields Bay SFCA employs eight full-time wardens from the community who maintain a twenty-four hour patrol. An estimated 160–200 fishers live in the vicinity of Bluefields Bay, largely in the coastal communities of Belmont, Cave, and Paradise. These fishers launch their boats from seven different landing sites (see Figure 1), which vary significantly in their size (~4–50+ fishers), composition with regards to gear type, and formality – i.e. only two of the seven landing sites are officially registered by the Fisheries Division.



Figure 1: Bluefields Bay Special Fishery Conservation Area and associated landing sites (Made by D. Campbell).

Here, the main function of the landing sites is to provide fishers a place to store and launch their fishing boat. Accordingly, landing sites provide access to the sea, as private landowners own the majority of the coast.

Previous research examining the social network among fishermen in Bluefields Bay found pockets of cohesion with significant fragmentation and numerous isolated fishermen (Alexander et al. 2015). In addition, the findings suggest that the presence of institutional entrepreneurs and a cohesive central core played key roles in supporting a transition to co-management (Alexander et al. 2015). However, the authors also note that the overall lack of cohesion (illustrated by the high fragmentation) may prove problematic for the long-term success of comanaged marine reserves. Accordingly, there is an imperative to understand what drives community cohesion in such settings.

3.2. Data collection

Social network data were collected via questionnaires administered through personal interviews with fishers (n=122). The target population (~163–197; see Appendix 7.1) was defined as all fishers based at landing sites located within the boundaries of the SFCA in addition to those landing sites directly adjacent to the boundary (n=7; see Figure 1). This resulted in a response rate ranging from 60 to 75%. To capture as complete a network data set of fishers as possible, lists of registered fishers provided by the Fisheries Division were coupled with lists of fishers produced by local community partners. Respondents from the list were also asked to suggest other fishers at each landing site. In addition, multiple visits to each landing site at varying times of day over the course of two weeks were made. This modified snowball sampling method was carried out until network closure had been reached – i.e. the addition and mention of new names is minimal, akin to saturation (Hanneman and Riddle 2005).

The network data collected were based on information-sharing ties. Specifically, respondents were asked whom they exchange information with concerning fishing and their time at sea – e.g. information related to fishing practices, locations, equipment, seasons, etc. (see Figure 2). Respondents were asked both whom they share information with and whom they receive information from (See Appendix 7.1 for the specifics of the survey question). All information-sharing ties - whether outgoing and/or incoming - were treated as binary (i.e. no directionality or strength). Questions capturing information-sharing ties employed a name generator with free recall, which asked respondents to list individuals (Marsden 2011). There was no upper limit placed on the number of individuals a respondent could nominate. Chua et al. (2011) note that this technique is well suited to capture strong ties. This method is particularly appropriate here as this study is concerned with community cohesion, which is reflected by the structural pattern and distribution of strong, beneficial ties - i.e. the ties provide the actors with different resources and possibilities (knowledge, feedback, etc.) that they value positively. Fishing activities and personal attributes of each respondent were also collected (e.g. gender, age, gear type, landing site). For specific details on the construction of the social network from the survey responses see Appendix 7.2.

3.3. Attributes

3.3.1. Gear type

Fishers in Bluefields Bay, Jamaica use one of four types of fishing gear: (i) hook and line; (ii) fish pot (i.e. traps); (iii) net; and (iv) spear gun. However, in some cases fishers use more than one gear type, in which case they would be defined as 'multi-gear'. Thus, gear type was operationalized as five binary variables so that any given fisher could only be assigned one gear type classification (See Figure 2D).

3.3.2. Landing site

In Jamaica, landing sites serve as social spaces where small-scale fishers are more likely to have repeated interactions with individuals on their way to go fishing or upon their return. While landing sites could be seen as a parallel exogenous network where a link corresponds to co-location (i.e. same landing site), here we operationalized this exogenous driver as seven binary attributes at the node level to reflect the seven different landing sites (see Figure 1) that bound the study site and network. Similar to gear type, fishers could only be assigned to one landing site (see Figure 2C).

3.3.3. Leadership

To examine leadership, we created a binary attribute at the node level that identified wardens (i.e. park rangers) embedded within the network (n=4). We considered wardens as leaders since they possess formal authority to cite infractions and in some cases held leadership positions in the fisher cooperative (See Figure 2B).

3.4. Exponential random graph modeling

Exponential random graph models (ERGMs) are statistical models developed for understanding network structure. As a class of stochastic network models, ERGMs are empirically informed, comparing observed, empirical networks with random networks (i.e. the null model). ERGMs are tie-based models – i.e. the focus is on processes and drivers that give rise to the formation and maintenance of network ties. This focus is operationalized through statistical analyses of the prevalence of different network building blocks (see Table 2), or network configurations composed of a few nodes and ties (Moreno and Jennings 1938). By linking certain building blocks with different tie formation processes (Table 2), a theoretically informed analysis of the structure of empirical networks can be conducted (see, e.g. Bodin et al. 2016).

One of the strengths of ERGMs is the ability to statistically account for overlapping and nested building blocks (Lusher et al. 2012). In this way, it allows for the examination and consideration of the complex combination of processes

General Parameter	
Edge	
Triadic Closure	
Alternating Triangle (ATA)	
<u>Homophily</u>	
Hook & Line Interaction	•••••
Net Activity*	N
Net Interaction	N-N
Spear Gun Interaction	SG — S G
Multi-Gear Interaction	MG-MG
Geographic Proximity	
Landing Site 1	0-0
Landing Site 2	12-12
Landing Site 3	L3-L3
Landing Site 4	L4-L4
Landing Site 6	16 — 1 6
Landing Site 7	0-0
<u>Leadership</u>	
Warden Activity	W — (

Table 2: Exponential random graph model configurations used for Models 1-5.

*Included as a control factor.

contributing to tie formation. Furthermore, nodal attributes can be incorporated as explanatory factors (Lusher et al. 2012).

Similar to regression analysis, the ERGM gives each of the examined building blocks a parameter estimate and a standard error. The sign of a parameter value is interpreted as whether the associated building block and the underlying processes giving rise to this building block, are either enhanced or suppressed in a given empirical network (Lusher et al. 2012). The standard error is used to assess statistical significance (Lusher et al. 2012). Building blocks whose parameters are not significantly different from zero would be interpreted as neither enhanced nor suppressed. It should be emphasized, however, that ERGMs are not regressions, most importantly because they take into account the dependencies that are implicit in network formation. Regressions assume independent observations – not well suited for the analysis of network structures – while ERGMs take into account the interdependency of network ties (Lusher et al. 2012).

3.4.1. Hierarchy of ERGMs

The underlying premise of using ERGMs is that overlapping and nested building blocks can be taken into consideration (Lusher et al. 2012). Hence, it is possible to disentangle the influences of entangled building blocks. However, ERGMs do not always converge. This often happens when the number of configurations included is high, though simple models can also suffer from convergence problems, especially if the models are not well specified – i.e. they do not represent the underlying tie formations processes well (Robins et al. 2012). Thus the ability to disentangle different effects is not always practically feasible. One way

Model	Description	Hypotheses
Model 1 Random model	The random model suggests that ties are both random and uniformly distributed across all fishers (Bernoulli model). Accordingly, the model only includes the general edge configuration – alternatively referred to as the density parameter	Baseline
Model 2 Triadic Closure	The triadic closure model builds on Model 1 through the inclusion of the alternating triangle (ATA) configuration and suggests that there is a structurally induced propensity of friends of a friend also being friends resulting in clustering and cohesion	H
Model 3 Triadic Closure + Homophily	The homophily model builds on Model 2 through the addition of a suite of gear-based homophily parameters. The resulting model considers the propensity for fishers to establish and maintain ties with others using the same fishing gear (e.g. spear gun, net)	$H_1 H_2$
Model 4 Triadic Closure + Homophily + Geographic Proximity	The geographic proximity model includes a series of parameters concerning landing sites. Building on Model 3, this model considers the propensity of geographic proximity to drive the establishment and maintenance of ties between fishers (or alternatively, drives fishers apart)	$\begin{array}{c} H_{1} H_{2} H_{3a} \\ H_{3b} \end{array}$
Model 5 Triadic Closure + Homophily + Geographic Proximity + Leadership	The leadership model adds the warden activity parameter and suggests that certain actors (i.e. wardens) will have more direct ties than the average actor	$\begin{array}{c} H_1 H_2 H_{3a} \\ H_b H_4 \end{array}$

Table 3: Descriptions of the sequential exponential random graph models (ERGM) developed and associated hypotheses.

to deal with this is to start with a simple model, and add more configurations incrementally (Table 3); making sure that convergence is reached at each step. Theoretically, this also makes sense in that in provides a way to investigate if the model performs better (i.e. is better able to represent the empirical data) as more configurations are added (see Bodin et al. 2016). In this context, it is important to point out this process should ideally be theoretically informed, i.e. that configurations should be added to the model if there are reasons to believe they are important, and not only through an unconditional search for configurations increasing model fit (cf. stepwise regression). Accordingly, we take an approach of developing a series of nested models (Table 3). Similar to Lubell et al. (2014), the approach seeks to build in additional complexity and assumptions.

We used MPNet software (Wang et al. 2014) for all ERGM. Model fitness was compared using the Mahalanobis distance measure developed by Wang et al. (2009). The Mahalanobis distance is a statistical measure that captures how far the observed network is from the center of a distribution of modeled networks (Wang et al. 2009). Accordingly, a smaller Mahalanobis distance suggests that the observed network falls closer to the center of the graph distribution generated from the model (Wang et al. 2009). In other words, a smaller distance indicates a better fitting model.

4. Results

Model 1 (*Random*) includes only an *edge* parameter (see Tables 2 and 4). This is, as expected, not a well-fitting model, as indicated by the relatively large Mahalanobis distance.

In Model 2 (*Triadic Closure*) we see a positive parameter estimate and significant standard error for the alternating triangle configuration (ATA, see Tables 2 and 4), which suggests a propensity for clustering and triadic closure. The reduction in the Mahalanobis distance of Model 2 as compared to Model 1 suggests that the inclusion of the triadic closure parameter significantly increases the fit of the model (Wang et al. 2009).

In Model 3 (*Triadic Closure + Homophily*) the parameter estimate is positive and significant for two of the gear types (i.e. net and spear gun) (Tables 2 and 4). The parameter is not significant for the other two (i.e. hook and line and multigear). This suggests that gear-based homophily contributes to tie formation and cohesion among some gear but not others. While the intention was to include all five-gear type interaction parameters for Model 3, the model would not converge when fish pot interaction was included. This is explained by the fact that only one fisher uses fish pots exclusively. All other fish pot fishers are captured in 'multigear.' Net activity was included as a control because it increased the ability to accomplish model convergence, which indicates it represents an important tie formation process in this context. Fishers using nets were significantly less socially connected across the entire community in comparison to others (demonstrated by the significantly negative parameter estimate for net activity, Table 4). However,



Figure 2: Information-sharing network among fishers in Bluefields Bay, Jamaica. Each circle represents a fisher, and the lines between them represent their information-sharing ties. Panel 2A illustrates the basic structure of the social network among fishers. Panels 2B–D each include one of the attributes of interest; (B) leadership; (C) landing site; and (D) gear type. The network visuals were generated using the Fruchterman-Reingold layout algorithm in the package igraph in R, where nodes are placed on the plane using this force-directed layout algorithm.

net fishers still showed a strong tendency to connect among themselves (demonstrated by the strong and significant effect of net interaction, Table 4).

In Model 4 (*Triadic Closure + Homophily + Geographic Proximity*), the geographic proximity parameter estimates are positive and significant for all landing sites included (Tables 2 and 4), suggesting they further contribute to the formation and maintenance of social ties. This mechanism is more enhanced for some landing sites (2 and 4) as compared to others. Model 4 would not converge with

	Model 1 Random model	Model 2 Triadic Closure	Model 3 Triadic Closure + Homophily	Model 4 Triadic Closure + Homophily + Geographic Proximity	Model 5 Triadic Closure + Homophily + Geographic Proximity + Leadership
General parameters Edge	-3.9846 (0.088)*	-4.7151 (0.118)*	-4.6725 (0.148)*	-5.2685 (0.164)*	-4.3228 (0.18)*
Triadic Closure ATA	I	1.2087 (0.085)*	1.048 (0.096)*	0.9088 (0.091)*	0.8402 (0.102)*
Homophily		~			
Hook and line interaction	I	Ι	0.3871 (0.319)	0.1735(0.351)	0.1849 (0.356)
Net activity ⁺	I	I	-1.2387 (0.592)*	-1.1896 (0.587)*	-1.1757 (0.584)*
Net interaction	I	I	3.4265 (1.576)*	2.6555 (1.437)*	2.6565 (1.457)*
Spear gun interaction	I	I	$1.0461 (0.162)^{*}$	1.2324 (0.198)*	1.3197 (0.218)*
Multi-gear interaction	I	I	0.1979 (0.192)	0. 2174 (0.2)	0.1331 (0.21)
Geographic Proximity					
Landing site 1 interaction	I	I	I	1.3195 (0.175)*	$1.4524 (0.192)^{*}$
Landing site 2 interaction	I	I	I	3.5227 (0.62)*	$3.7323 (0.623)^{*}$
Landing site 3 interaction	I	I	I	1.6137 (0.188)*	$1.4161 (0.209)^*$
Landing site 4 interaction	I	I	I	2.6917 (0.383)*	$2.8058 (0.419)^{*}$
Landing site 6 interaction	I	I	I	$2.0963 (0.31)^{*}$	$2.0015 (0.326)^{*}$
Landing site 7 interaction	I	I	I	$1.7764 (0.231)^{*}$	1.9387 (0.226)*
Leadership					
Warden activity	I	I	I	I	$0.8948 (0.21)^{*}$
Mahalanobis distance	26,189,363	1,656,063	100,893	6,963	4,203

Table 4: Results from nested exponential random graph models.

Parameter Estimate (Standard Error); *Reject null hypothesis of parameter=0, p<0.05: *included as a control factor.

parameters for all 7 landing sites. As a result, landing site 5 was not included (Table 4). However, based on a residual analysis, all landing site configurations seemingly deviate in a significantly positive manner from what would be expected in a random network (i.e. their t-ratios were >2.0, see Appendix 7.3 and Lubell et al. 2014). All parameters that were significant in Model 3 are still significant. The reduction in the Mahalanobis distance of Model 4 as compared to Model 3 suggests that the inclusion of geographic proximity parameters significantly increases the fit of the model (Wang et al. 2009).

In Model 5 (*Triadic Closure* + *Homophily* + *Geographic Proximity* + *Leadership*) the leadership parameter estimate (i.e. warden activity) is positive and significant, suggesting that wardens tend to have more ties than would be expected by chance (Tables 2 and 4). Leadership thus contributes to the emergent network structure, alongside geographic proximity, and gear-based homophily. Based on a comparison of the Mahalanobis distance, Model 5 is the best-fitting model. Also note that the parameter estimate for ATA reduces when geographical proximity and warden activity is accounted for, demonstrating that triadic closure is in part explained by space and by wardens serving as "local hubs", thereby increasing the likelihood for triangles to form (Table 4).

5. Discussion

5.1. Triadic closure and social capital

Granovetter (1973) suggested the general tendency for friends of a friend to be friends. Since then, this process of triadic closure has emerged as one of the most common structurally driven tie formation processes (Hammer 1980; Kossinets and Watts 2006). The significant effect of triadic closure (i.e. the alternating triangle configuration, ATA) found here suggests the presence of clustering and bonding social capital (see, e.g. Berardo 2014). Such social fabric (i.e. bonding social capital) within communities reduces transaction costs and contributes to the development of trust (Friedkin 2004). Furthermore, the sharing of multiple ties among a set of resource users (exemplified by the ATA configuration) provides the "social infrastructure" necessary to facilitate the development of commonly agreed upon harvesting rules and contributes to self-monitoring (Ostrom 1990; Pretty 2003; Berkes 2010; Nunan et al. 2015).

However, it is important to note that a positive tendency for triadic closure does not mean all actors are necessarily confined in one large coherent cluster. For example, a strong tendency for triadic closure could also lead to the establishment of a set of more or less isolated islands in the network. As Alexander et al. (2015) and Bodin and Crona (2009) note, such pockets of bonding social capital within a sparse and fragmented network may prove problematic in the long term for sustaining new governance arrangements, such as co-management, because it can cause different groups with competing interests to form. Hence, albeit the presence of triadic closure seems beneficial from a bonding social capital point of view, it does not by itself equate with cohesiveness on the whole network level. Moreover, there is also a potential 'dark side' of having too much bonding social capital (Di Falco et al. 2011). This reflects the fact that high levels of social cohesion can sometimes cause people to become locked into current trajectories, leading to the rejection of new ideas, information, and knowledge that may prove necessary to effectively adapt to changing social and ecological conditions (Barnes et al. 2017b).

5.2. Gear-based homophily

Success as a small-scale fisherman in a heterogeneous and highly dynamic environment requires tacit knowledge (Crona and Bodin 2006). Accordingly, our results demonstrate that some fishers tend to seek and share information with others whose experiences and resource needs are similar – i.e. there is a tendency for gear-based homophily, which supports findings from other SSF (e.g. Crona and Bodin 2006; Cox et al. 2016). The type of gear fishers use is often associated with their social identity (Miller and Van Maanen 1982) and a more distinct form of occupation than the broader category "fisher" (Crona and Bodin 2006). These are both well known for structuring homophilous social interactions, i.e. social ties with others who are similar (McPherson et al. 2001), where tacit knowledge transfer is thought to be enhanced (Cross et al. 2001).

In contrast to previous inquiries in SSFs, we found that not all gear types demonstrate homophilic tendencies. Specifically, we found that hook and line and *multi-gear* fishers did not display significant homophily, which may in part be explained by the nature of these fishing activities. The use of hook and line in near-shore reef fisheries in Jamaica is a fairly solitary endeavor, often done at night. In contrast, fishers often fish in groups when using other types of gear, which is more likely to promote social cohesion since it requires cooperation and motivation to contribute to the group's success (Friedkin 2004). In this case multigear, on the other hand, equates to a fisher using anywhere between two and four different gear types. Accordingly, whom fishers have tendencies to form a tie with may depend upon which of those gears is their primary gear type (e.g. fishers who primarily use fish pots may have a tendency to form a tie with other fish pot users - yet unfortunately we did not collect this information). Multi-gear users may also be more prone to forming ties with a diverse array of fishers using different gear types to better buffer against the complexity of situations encountered when applying different fishing techniques. This implies that multi-gear users may be key for promoting greater connectivity across different types of fishers, thereby having a positive impact on community cohesion.

5.3. Geographic proximity

Geographic proximity is another common driver of social tie formation (Gieryn 2000; Rivera et al. 2010; Lusher et al. 2012). Much of the previous work focused on geographic proximity and social ties in SSF relates to fishing grounds (e.g. Maya-Jariego et al. 2016). To this end, for example, Martin and Hall-Arber (2008)

speak of the emergence of "communities at sea." However, these fisheries are offshore using larger boats, reflecting a very different context than that most often found in SSF. For example, in near-shore, reef-based SSF, fishers are hardly more than a few kilometers from shore. In Bluefields Bay, Jamaica, they are rarely more than a kilometer from shore. Accordingly, landing sites reflect a form of geographic proximity and serve as social spaces where fishers are likely to have repeated interactions with individuals on their way to and from fishing at sea. Furthermore, fishers often spend prolonged periods of time at the landing sites socializing, repairing fishing gear, and cooking after they return from the sea. Thus, landing sites are social spaces that facilitate prolonged engagements rather than fleeting interactions. Indeed, we find that across the landing sites, proximity plays a significant role in structuring interactions.

Place-based interactions can play a significant role in fostering a sense of place and contributing to community cohesion. For example, Brown (2015) found that fishing wharfs in Cape Brenton, Nova Scotia contributed to supporting and maintaining social connections among fishers. In combination with our findings, this suggests that landing sites – in the broadest sense – provide an entrée for supporting local institutions, building a sense of place, and fostering community cohesion.

However, the strong tendency for social ties between fishers at the same landing site (i.e. positive parameter for geographic proximity) coupled with the clustering of ties (i.e. strong tendency toward triadic closure) is problematic for community cohesion as it suggests the potential for fragmentation between landing sites. Indeed, Alexander et al. (2015) note an "us vs. them" mentality between some of the landing sites posing a significant barrier to collective action. This suggests that strengthening community cohesion will require actively building ties across landing sites – perhaps a role for wardens or other community leaders.

5.4. Leadership

The presence of local community leaders serves as another driver of social tie formation. As leaders are sought after for their information, influence, and power associated with their position and experience, they accrue more ties on average than others. In our case, we find that being a warden is a strong predictor of social ties, suggesting that leadership executed by wardens is particularly strong. Furthermore, residual analysis indicates that the model adequately captures all hubs – i.e. no actors other than the wardens tend to be acting as hubs. At the outset, we identified possible hubs by an attribute (i.e. being a warden). However, through residual analysis we test our *a priori* assumptions by taking a relational perspective to see whether all hubs are captured by the configuration of warden activity (See Appendix 7.3) – which it does. These results may well reflect the presence and role of the local fisher cooperative where some of the wardens have formal leadership roles. Accordingly, this raises the question as to whether wardens are popular because of their role in the cooperative, or because of their

status as park rangers involved in monitoring and enforcement. Though existing research from this region suggests that wardens whom also hold a leadership position in the cooperative are even more popular (i.e. higher number of direct ties) than wardens who do not (Alexander et al. 2015).

Community leaders (i.e. wardens) are not only a driver of social tie formation; they also interact with community cohesion in important ways. When community cohesion is considered as a latent resource or asset, then community leaders can bring people together to activate the latent cohesion necessary for collective action and the successful management of common-pool fisheries resources (Crona et al. 2017). On the other hand, local community leaders can also be involved in elite capture – defined here as situations where certain individuals dominate decision-making and in turn disproportionally improve their access to benefits from common-pool fishery resources (*sensu* Ribot 2007). In such instances, 'leadership' can have the complete opposite effect, whereby community cohesion erodes and fragmentation amplifies. Accordingly, elite capture and perceived legitimacy are important considerations for effective governance approaches where local users play a significant role (e.g. local, traditional, or co-management).

5.5. Cooperation and competition in SSF

By its very nature, the foundation of community cohesion implies some level of cooperation among individuals who actively make decisions to form cooperative social ties with others. Understanding the tendencies towards cooperation is of particular interest in the context of common-pool resource systems such as SSF, as competition over shared resources is a critical issue that has to be overcome in order to manage them sustainably (Hardin 1968; Ostrom 1990; Salas and Gaertner 2004). Importantly, two configurations from our final model suggest that in this case, there are higher levels of cooperation than competition. The first is the strong tendency toward triadic closure, indicated by the positive ATA parameter (Table 4). The second is the overwhelming persistence of a positive parameter for geographic proximity across landing sites. We discuss both of these further below.

Cooperating in SSF is a risky business – e.g. some might decide to take the information they receive from others to enrich themselves without reciprocating – due to the heterogeneity of marine environments, dynamic variability of fisheries, and the general lack of secure 'property' rights (Wilson 2006). Thus, if fishers are to truly cooperate, existing theoretical and empirical research suggests that they would seek to establish bonding relationships characterized by trust when the risk of defection increases (Berardo and Scholz 2010). The general high risk of cooperation in SSFs is in contrast to less-risky problems such as coordination where the cost of deflection is low and thus bonding relationships are not as essential. Hence, the strong presence of triadic closure suggests that fishers use their ties for cooperative purposes related to their profession as fishers.

The persistence of a positive parameter for geographic proximity across landing sites also provides insights regarding cooperation. Fishers that compete over shared resources at a given landing site might be one's fiercest competitors, but they are also fishers that one repeatedly encounters and likely interacts with, creating an obvious tension (e.g. Basurto et al. 2016). This tension leads to our two contrasting hypotheses, 3A and 3B: (3A) the social closeness outweighs the competitive pressure (positive parameter) suggesting cooperation; or (3B) fishers avoid their fiercest competitors (this would imply a negative parameter for binaryhomophily based on landing site). Accordingly, the positive parameter found here indicates that there is more of a cooperative rather than antagonistic atmosphere at landing sites – or put another way, fishers choose their cooperators from their fiercest competitors.

One can further envision interplay between triadic closure and geographic proximity here. If you were to choose your cooperators among your fiercest competitors, the risk of engaging in cooperation would most likely be deemed as high. Hence, that would further emphasize the propensity to form cooperative ties in ways that minimize the risk for defection, i.e. triadic closure. Hence, by considering the strong and significant effects of triadic closure and geographical proximity together, further support is provided for Basurto and colleague's (2016) recent suggestion that competition and cooperation to some extent co-evolve. Accordingly, it is plausible that if increased competition coincides with social changes that reduce social cohesion and trust (e.g. polarization, loss of sense of place, etc.), fishers would be less inclined to respond to increased competition with increased cooperation. In such cases, competition might outcompete cooperation, which likely reduces the fishers' collective abilities to manage their common good, and could initiate a vicious cycle of accelerating overharvesting and competition (i.e. a race to the bottom) (Hilborn et al. 2005, Costello et al. 2008).

6. Conclusion

Community cohesion forms an important foundation for the emergence and maintenance of key social processes that support effective resource governance, such as collective action, coordination, and learning. Indeed, fragmentation and low social cohesion can undermine collective action and contribute to undesirable outcomes (Crona and Bodin 2010; Barnes-Mauthe et al. 2013a; Barnes et al. 2016). Where state support is weak, the social ties that bind communities together (i.e. social networks) – and associated aspects of leadership and social capital – can be critical for effectively organizing actors to get together to devise, implement, and maintain local institutions and institutional arrangements (Ostrom 1990; Pretty 2003). This is particularly evident when it comes to co-management of SSF (Gutiérrez et al. 2011; Pomeroy and Andrew 2011; Cinner et al. 2012).

In complex common pool fishery resource settings such as SSF, existing research has shown that multiple drivers are at play that contribute to the establishment and maintenance of social ties, e.g. the type of gear fishers use (Crona and Bodin 2006) and ethnicity (Barnes-Mauthe et al. 2013a). These patterns of social relationships have implications for the sharing of information, adoption of new norms and behaviors, and compliance with rules (Friedkin 1998; Frank 2011; Barnes et al. 2016). Yet untangling the drivers of social cohesion and fragmentation in SSF, characterized as multi-gear and multi-species, has been understudied.

Here we identified the underlying processes (micro-level social interactions) that lay the foundation for community cohesion in SSF, and discussed their implications for effective governance more broadly. In line with previous research (Crona and Bodin 2006; Cox et al. 2016), we demonstrated that the type of gear fishers use contributes to explaining the formation and maintenance of social ties. We also show that community leadership (i.e. wardens/park rangers with employment overlooking fisheries activities in this case) promotes network activity (i.e. they sustain many social ties with fishers). While this does not rule out the existence of other forms of leadership, in our case, wardens unarguably uphold influential positions in fishers' information sharing networks. Finally, we demonstrate an interesting interplay between geographic proximity and cooperation and competition (cf. Basurto et al. 2016). Our results suggest cooperation and competition may to some extent be co-evolving, as fishers seemingly do not shy away from engaging in in-depth cooperation with those whom may be considered their fiercest competitors. As illustrated here, this study and the approach leveraged allows for the in-depth investigation of key social processes at play and helps to provide critical insights regarding the drivers of community cohesion in SSF.

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7. Appendix

7.1. Data collection

Total number of fishers across Jamaica is not well known. In order to establish an initial target population of fishers to survey with additional snowballing we combined two lists of fishers. The first was a list compiled by a local communitybased organization and the second was a list of *registered* fishers provided by the Division of Fisheries. We then returned to these two lists to cross-reference names of fishers who were identified as individuals who the survey respondents either shared or received information from. Due to the lack of data, we used the network survey responses as a way to establish a range for the target population.

Total # of fishers surveyed	130	
Total # of fishers surveyed from target landing sites	122	
Total Alters* not surveyed	106	
Alters* outside the network boundaries		
Organizations/agencies	7	
Individuals from organizations/agencies	8	
Fishers from other landing sites	13	
Total outside network	28	
Total inside network	41	
Unknown	34	
	Target population	Response rate
Low-end total (total from target landing site + inside network)	163	74.8%
Upper-end total (total from target landing site + inside network + unknowns)	197	59.5%

*Alters refers to the names of individuals and/or organizations that a person being surveyed identifies as sharing or receiving information from.

7.2. Network construction

To collect social network data respondents were asked whom they share information with and whom they receive information from. These responses were cross-referenced to create the resulting social network (i.e. matrix). Two things are important to note. The first is that while the responses provide directionality for a given tie, we created a non-directed network – reflecting the presence or absence of a tie between two fishers – to simplify the ERGM. The second is that while ERGM can handle directed ties and configurations exist that incorporate directionality; it would have significantly increased the number of configurations that would have been needed to be included in the model development.

7.3. Exponential random graph model development, analysis, and interpretation

7.3.1. Residual analysis

Residual analysis involves an examination of a configuration's t-ratio from the Goodness of Fit results and can be used in a few different ways. It can be used to consider whether an omitted configuration (perhaps due to issues of convergence) would have been significant if included (indicated by a t-ratio <2).

Similarly, residual analysis can be used to test model assumptions. For example, to see whether 'warden activity' adequately captured all of the hubs (i.e. well connected leaders), we used residual analysis to see if the model adequately captures the 2-star configuration – which also reflects a hub. If this configuration were not adequately explained by the configurations included in the model – specifically warden activity – then we would need to revisit our assumptions regarding wardens being an adequate representation of leaders in this case. Note that the results suggest that statistically ERGM does not pick up other hubs. However, the distribution of ties among actors is not even – as to be expected – and thus there are other actors with above average ties (see Figure 2) who may also be a 'hub.'

Residual analysis can also be used to evaluate your model fit by examining the t-ratio for all configurations included in the model (indicated by a t-ratio <0.2). See Lubell et al. (2014) for additional details.

7.3.2. Control factors

While the theoretical focus of Model 2 was on homophily, which is captured via 'interaction' configurations, *NetActivity* was included as a control factor to improve model fit. Without the *Net Activity* configuration, residual analysis of the t-ratio reveals that the configuration is not well captured in the model (t-ratio=-2.059). However, when *NetActivity* is included in the model as a parameter, the Goodness of Fit is much better when comparing the resulting Mahalanobis distance (Md). Without *NetActivity* the Md is 296,023 while the inclusion of *NetActivity* results in an Md of 100,893. Furthermore, because of the nested model approach the parameter continued to be included.

7.3.3. Models 4 and 5

Models 4 and 5 did not converge during the model estimation phase despite an increase in multiplication factor of 60 (see Wang et al. 2014). However, instead we ran the Goodness of Fit simulation with 10 times the number of suggested iterations. A residual analysis examining configurations included in the model confirmed that the model was a good fit (t-ratios smaller than 0.1 in absolute value; see Wang et al. 2014).