8

Social network models for natural resource use and extraction

8.1 introduction: orientation to network analysis for natural resource usage

The analysis of social networks has tremendous capacity to inform social science and policy about how people extract natural resources (e.g. Prell et al., 2009). Attention to social networks frees us from the typical assumptions that individuals act independently or are independent conditional on membership in common organizations (Frank, 1998). Instead attention to social networks embraces the relational (Emirbayer, 1997), and, as it does so, provides a potential bridge between different disciplines and modes of research.

Although social network analysis has great potential to help us understand the causes and consequences of natural resource usage, there are important limitations and pitfalls of which social scientists must be aware (Wellman & Berkowitz, 1997; Degenne and Forse, 1999; Scott, 2002; Breiger, 2004; Freeman, 2004; Carrington et al., 2005; Wasserman and Faust, 2005). In this chapter I will suggest that expressing theory and analysis in formal social network models can help social scientists realize the potential of social network analysis, contributing to scientific dialogue about the effects of, and on, social networks.

8.1.1 Example: The Maine lobster fishery

I anchor my presentation in the case of the Maine lobster fishermen. This is one of the most well-known communities of fishermen, with
special potential for network effects (Acheson, 1988), many of which are quite current (e.g. MSNBC, July 21, 2009). The American lobster fishery has been strikingly robust when compared with other fisheries (Acheson, 1988; Frank et al., 2007). Prior to 1950, lobsters were taken offshore primarily as incidental trawl catches in demersal fisheries (living on or near the bottom of a sea or lake). Reported offshore lobster landings increased dramatically from about 400 metric tons (mt) during the 1950s to an average of more than 2000 mt in the 1960s. In 1969, technological advances permitted the introduction of trap fishing to deeper offshore areas, which helped to increase landings (trap landings: 50 mt in 1969 to 2900 mt in 1972). Total landings were steady from 1977–1986 (~17,600 mt/year). In the 1990s, with improved distribution and market, the landings increased to approximately 32,000 mt per year with a slight decline in 1992–1993. Thus far, the lobster fishermen have not experienced the drop-off in catches indicative of overfishing as in the case of other fisheries (Acheson, 2003; Frank et al., 2007).

The question arises as to why the Maine lobster fisheries, despite what appears to be increased fishing effort, have not experienced declines in their target species as have been typically experienced in other fisheries. Though the answer is complex, involving a range of ecological and social factors, one critical factor resides in the social relations of the local fishermen. Indeed, Acheson (1988, 2003) specifically credits the lobster fishermen’s social relations as central to the successful management of the fishery.

The social relations of Maine lobster fishermen are organized within harbor-based gangs (Acheson, 1988). To defy the gang is to risk ostracism, a serious sanction because a fisher’s success often depends on social support of others as well as the exchange of local and long-held knowledge regarding fishing. Furthermore, since the gangs are defined by long-standing social and kin-based relationships, ostracism affects an individual’s social standing in the community as well as his ability to make a living.

The lobster gangs draw on their social relationships to aggressively protect their territories. If a fisher places traps in a harbor perceived to be the territory of a rival gang, the rival gang members will either first warn the intruder (verbally or by notching the trap) or sabotage the perceived intruder’s traps (e.g. cutting the traps, placing debris in them). The social structure of the gang is critical to perpetrating the sabotage and punishing the intruder. It often takes several members to challenge a potential intruder, and all members of the gang are complicit in their support of the saboteur. Although there are
temptations to “second order free-ride” from enforcing sanctions, ultimately the gangs sustain a norm of territorial control (Acheson 1988, 2003). This territorial control effectively limits the number of traps local and non-local fishermen can place in the water, with indirect effects on the sustainability of the resource (Acheson, 1988, 2003; Frank et al., 2007).

Compare the Maine lobster fishery with the Western Atlantic spiny lobster (Panulirus argus) fishery of the Turks and Caicos Islands (TCI). Like the Maine lobster, the spiny lobsters live close to shore and have limited mobility and it is relatively easy for fishermen to observe and limit each others’ trap placements (Frank et al., 2007). Politically, Haitians, Dominicans, and other “non-belongers” are not allowed to commercially fish unless a “belonger” (i.e. Island national) is aboard the vessel with them at all times; akin to having the approval of the TCI community. On the whole, the social model of the TCI lobster shares many characteristic with that of the gangs of Maine lobster fishermen. However, in TCI, unlike in the Maine fishery, there is widespread acknowledgement of a general lack of enforcement of illegal fishing activities. As a result, foreign poaching vessels and fishermen outside the TCI community regularly enter the fishery and take lobsters with little or no restraint so that the TCI spiny lobster fishery has deteriorated while the Maine lobster fishery has remained sustainable.

It is beyond the scope of this chapter to say for sure whether the TCI spiny lobster stock could have been better managed had the TCI fishermen a more extensive and cohesive social network, drawn from community membership, to enforce fishing practices (see Davis et al.’s (2006) critique of Acheson’s conclusions). However, the TCI circumstances provide additional motivation for our use of the Maine lobster fishery to explore the underlying network models that can affect natural resource usage.

### 8.1.2 Research questions related to social networks and natural resource usage

Good social science starts with good research questions. Therefore I present two fundamental research questions that one might pose with respect to social networks and the use of natural resources. The first question concerns how an actor is influenced by members of his or her network. In the example of the Maine lobster fishery, this might take the form of how the members of a fisherman’s network influence the technology he uses for fishing, such as a the number and location of
traps he places in the water. The second question concerns how people choose or select with whom to interact. In the example this might concern with whom senior knowledgeable lobster fishermen, known as highliners, share their knowledge of where to place traps. I will use these questions to identify limitations and pitfalls of social network analysis and then relate them to formal models that can inform social science theory and discourse about natural resource usage.

8.1.3 Limitations and pitfalls of social network analysis

I begin with two limitations of network analysis concerning the nature of social network data, about which the social scientist must make defensible decisions (other limitations can be found in Knoke and Yang, 2008: chapter 3; Wellman and Berkowitz, 1997). The first limitation concerns the uncertainty of the network relation or tie through which actors are influenced. Are natural resource users influenced by all those with whom they come in contact, or are there specific types of relations that are more influential for particular behaviors? Generally, kinship is a basis of some of the most important ties in subsistence communities (e.g. Levi-Strauss, 1969; Landa, 1994; Bearman, 1997). In the example of lobster fishermen, those with kin in a given community are more likely to be accepted by the community (Acheson, 1988: chapter 2). But even kinship is not an unambiguous basis for a tie, as the definition of kin may vary across cultures or even in the perceptions of members of a given community. Consider the recent dispute in which one Maine lobsterman considered himself a community member by virtue of his marriage while another did not consider him so (New York Times, 2009). Moreover, even if kinship was agreed upon, important relations can emerge through intense socializing experiences that cut across kinship barriers (Acheson, 1988: 58). These other relations could convey knowledge or norms that influence the behavior of natural resource users.

The second limitation concerns the definitions of the network boundary (e.g. Zuckerman, 2003; Marsden, 2005). How does one define the relevant boundary from which actors may choose network partners? For Maine lobster fishermen, the answer may seem straightforward because they live and work in communities defined by the geographies of harbors (Acheson, 1988). And yet “many highliners go out of their way to initiate and maintain ties with highline fishermen in nearby communities to exchange information and ideas” (Acheson,
In other examples the definition of the boundary may be considerably more problematic. Should the network of a natural resource user include anyone who might influence his behavior or with whom he might interact?

The pitfalls of social network analysis emerge more from analytic practices than from fundamental limitations in the data. One pitfall in social network analysis is the inclination to disconnect social network analysis from other forms of analysis. Social network effects should be included alongside other effects (Doreian, 2001; also see Chapter 3). For example, in studying the effect of a lobster fisherman’s network on his fishing behaviors, one must also account for the lobsterman’s knowledge of the fishery and economic conditions. As one lobsterman put it in the negative, when prices are low “it wouldn’t do us any good to catch more lobster because if we do, it’ll drive down the prices even more” (USA Today, 2008; see also Acheson, 1988: 156).

A second pitfall is the attraction of rendering social networks in attractive pictures such as sociograms without systematically estimating the relationships between networks and individual behaviors. As Zuckerman states in the organization theory blog:

> One of the features of social network analysis that is at once a great strength and a great danger is that network diagrams are highly evocative. In teaching and presenting network material, I have found that if I put up a picture of a network and start spinning a story about it, even untutored audiences follow along easily and they tend to accept the network as an accurate characterization of the actors and the social structure they inhabit. This is great, but the problem is that any such presentation tends to bake in all kinds of assumptions that should always be questioned. (Zuckerman, 2008)

Zuckerman’s concern is an example of the need to push social network analysis beyond mere graphics and metaphor (Breiger, 2004).

I recognize that graphical representations of network data can be helpful in developing theory or expressing data in accessible form, especially of systemic phenomena. Indeed, my entry into network analysis came primarily through my technique, KliqueFinder, for embedding subgroup boundaries in sociograms (Frank, 1993, 1995, 1996, Frank and Yasumoto, 1996).

For example, Frank and Yasumoto (1998) identified cohesive subgroups based on friendships among the French financial elite (software available at http://www.msu.edu/~kenfrank/software.htm). After using simulations to establish that the friendships were concentrated...
within subgroup boundaries at a rate that was unlikely to have occurred by chance alone, they embedded the boundaries in a sociogram (see Figure 8.1). In this sociogram, each number indicates a member of the French financial elite (e.g. chief executive officers of major public or private financial institutions) with the circles representing subgroup boundaries. The lines indicate a friendship between

![Sociogram of friendships among the French financial elite](image)

**Figure 8.1** Crystalized sociogram of friendships among the French financial elite (Frank and Yasumoto, 1998). Reprinted with permission from University of Chicago Press.
two people; solid lines within subgroups, dashed between. Distances between actors and subgroups are indicative of patterns of friendship ties, with shorter distances representing denser sets of friendships. Thus the subgroups represent a social space defined exclusively by the pattern of interaction in contrast to kinship or geographic boundaries assumed for the fishermen.

Frank and Yasumoto then showed that resource allocations varied with the subgroup boundaries. First, hostile actions (e.g. a corporate takeover) almost never occurred within subgroups, indicating that trust could be enforced via the dense friendships within subgroups. Second, supportive actions (e.g. large short-term loans in response to informal requests), were more likely to occur amidst the sparse ties between subgroups. Frank and Yasumoto reasoned that members of the French financial elite supported others outside their subgroups because they already had social capital within their subgroups via enforceable trust – the dense social ties within subgroups increased the likelihood that anyone who betrayed the trust of a subgroup member would be sanctioned, socially and otherwise, by the subgroup as a whole. Thus members of the French financial elite sought to engender new obligations and access new information and resources by helping those outside their subgroups.

The sociological forces affecting the French financial elite may seem far removed from those forces experienced by those who rely on natural resources for their livelihood. And yet both types of economies are generated by allocation and movement of what are potentially common resources, be they fiscal or natural. In fact, the allegorical tragedy of the commons generated as community members use public grazing land solely for their own good (Hardin, 1968) could as easily apply to members of the French financial elite who directly and indirectly manipulate the financial coffers of France for political or reputational gain.

The methodological contribution of Frank and Yasumoto is that they moved beyond mere graphical representation by specifying the relationship between the friendship structure and hostile or supportive actions in formal models of how actors selected others for hostile or supportive action. They then estimated the size of the subgroup effects while controlling for other factors such as attendance at a common post-secondary school or membership in the same political party. Thus Frank and Yasumoto were able to demonstrate an effect of subgroups above and beyond correlates of subgroup membership based on similar career experiences or political affiliations. In the
next section I will provide a general example of the models used by Frank and Yasumoto and refer to software for estimating those models.

Generally, the limitations and pitfalls of social network analysis reduce to issues of causal inference (Wellman and Berkowitz, 1997; Doreian, 2001). How confident are we that actors are influenced by the other actors through relations we have measured? How confident are we that actors selected others with whom to interact and were not simply influenced by other common factors? While there are many solutions and approaches the network analyst could take to address these questions, in the next section I show how expressing network effects within formal models can support social scientists’ causal inferences by helping them mitigate limitations and avoid pitfalls.

8.2 THE FUNDAMENTAL MODELS FOR SOCIAL NETWORK ANALYSIS: INFLUENCE AND SELECTION

The model of influence expresses how actors’ beliefs, knowledge or behaviors are affected by the others with whom they interact. This would apply, for example, to how the number of traps a lobster fisherman places in the water is influenced by the norm in his community. The model of selection specifies how actors select with whom to engage in interactions. For example, how do the senior lobster fishermen choose to whom to give advice or support to enter the lobster fishery? These choices affect the distribution of knowledge as well as the potential to create new knowledge through interaction (Schumpeter, 1934). Together models of influence and selection represent processes through and on a social network.

8.2.1 Influences on a fisherman’s natural resource usage

I begin by modeling a fisherman’s behavior as a function of the behavior of others with whom he interacts (as a norm), his knowledge, the gear he owns, and his own prior behaviors. For example, let sustainable practices represent the extent to which fisherman i engages in sustainable practices. For lobster fishermen, sustainable practices might consist of use of traps instead of trawling (National Fisherman, 2007), and the use of a modest number of traps. I model the fisherman’s sustainable practices as
sustainable practices\(_i\) = \(\beta_0 + \beta_1\) exposure to previous sustainable practices of others in the network of person \(i\) + \(\beta_2\) knowledge of natural resource\(_i\) + \(\beta_3\) gear owned\(_i\) + \(\beta_4\) previous sustainable practices\(_i\) + \(e_i\) \hspace{1cm} (1)

where the error terms (\(e_i\)) are assumed independently distributed, \(N(0,\sigma^2)\). In (1), "exposure to previous sustainable practices of others in the network of person \(i\)" refers to the previous behaviors of those with whom actor \(i\) interacts. Thus if fisherman Bob interacts with Al and Joe who engage in sustainable practices at levels of 8 and 10 respectively (for example, these might be the number of days per year they exceed a trap limit), then Bob is exposed to a norm of 9.\(^1\) Given this definition of the exposure term, \(\beta_1\) indicates the normative influence of others on fisherman \(i\). This normative influence can be understood as an effect of social capital that complements the fisherman’s human capital (knowledge) and physical capital (the gear he owns).

Note that model (1) can be estimated as a basic regression model, with a term representing the network effect (Friedkin and Marsden, 1994). As such, and given longitudinal data, the model can be estimated with ordinary statistical software (e.g. SAS, SPSS) once one has constructed the network term (see [http://www.msu.edu/~kenfrank/resources.htm](http://www.msu.edu/~kenfrank/resources.htm) [influence models] for SPSS and SAS modules and power point demonstration that calculate a network effect and include it in a regression model). Therefore, within the regression framework one can examine the effects of social networks alongside effects of other theoretically recognized factors, addressing pitfall 1.

Note the use of timing to support the causal inference by identifying the effects in model (1). First, controlling for an actor’s own prior behavior accounts for the tendency for actors to interact with others similar to themselves (selection based on homophily); the portion of influence that can be attributed to an actor’s tendency to interact with others like himself is removed by controlling for the actor’s prior attributes including behavior (or beliefs).

\[^1\] This definition of exposure extends basic conceptualizations of centrality by accounting for the characteristics of the actors to whom one is exposed. Thus the focus shifts away from the structural towards flows of those attributes or related resources.
Second, the influence effect is specified as a function of a fisherman’s peers’ prior characteristics. This would be natural if one were to model contagion. For example, whether I get a cold from you is a function of my interaction with you over the last 24 hours and whether you had a cold yesterday. I would not argue that contagion occurs if we interacted in the last 24 hours and we both get sick today (see Cohen-Cole and Fletcher’s (2008b) critique of Christakis and Fowler’s (2007, 2008) models of the contagion of obesity; see also Leenders, 1995).

A key issue in specifying model (1) is to identify the relevant network of ties for fisherman \(i\), limitation 1. In the context of the influence model, one should measure the relation through which influence flows will affect a specific behavior. That is, priority is given to the behavior of interest, and the network relation defined relative to that behavior. For example, if one is modeling the extent to which a fisherman engages in sustainable practices then one might use network relations through which fishermen would be exposed to others’ practices or knowledge such as through observation or conversation. One would not use others with whom a fisherman went to school unless such ties also conveyed resources relevant to current fishing behaviors. Thus limitation 1 is addressed by making a scientific argument relative to the influence process of interest.

Importantly, the influence model does not confine the researcher to estimating influence through a single relation. Friendship defines one possible source of exposures for an actor. Clearly another for subsistence natural resource users would be kinship. Building on the standard network effects model, one could estimate separate effects for the influences of kin versus friends (Doreian, 1989):

\[
\text{sustainable practices}_i = \beta_0 + \\
+ \beta_1 \text{ exposure to previous sustainable practices of friends}_i \\
+ \beta_2 \text{ exposure to previous sustainable practices of kin}_i \\
+ \beta_3 \text{ knowledge of natural resource}_i \\
+ \beta_4 \text{ gear owned}_i \\
+ \beta_5 \text{ previous sustainable practices}_i \\
+ \epsilon_i. 
\]  

(2)

The terms \(\beta_1\) and \(\beta_2\) then represent the separate influences of friends versus kin, and the difference between \(\beta_1\) and \(\beta_2\) indicates which set of influences are stronger and can be tested via a standard test of the
difference between two regression coefficients (Cohen and Cohen, 1983: 111).2

Networks can also be extended beyond direct interactions (limitation 2). For example, one could construct an exposure term based on others whom a fisherman observed, members of a fisherman’s cohesive subgroup (where relations are concentrated within cohesive subgroups, but not all members of subgroups have relations with each other – see Figure 8.1), or with whom the fisherman casually interacts. That is, the network can extend beyond direct ties with whom an actor is friends or kin.

Network effects beyond those of direct relations will quickly become difficult to measure and differentiate, especially in small closed communities which allow extensive opportunities for casual interaction and observation of all in the system. One way to model the influence of all in the community is through multi-level models. Multi-level models are a large class of models for estimating effects of nested data such as individuals within organizations (see Raudenbush and Bryk, 2002). As such they have been employed in social network analysis (Frank, 1998; Frank et al., 2008) and have been at the root of some methodological advancements in social network analysis (Lazega and Van Duijn, 1997; Van Duijn et al., 1999; Wellman and Frank, 2001). For example, I can extend (1) to a multi-level framework for fisherman i nested within community j:

At Level 1 (individual level i in community j):

\[
\text{sustainable practices}_{ij} = \beta_0 + \beta_1 \text{ exposure to previous sustainable practices of others in the network of person } i_{ij} + \beta_2 \text{ knowledge of natural resource}_i + \beta_3 \text{ gear owned}_i + \beta_4 \text{ previous sustainable practices}_i + \beta_2 \text{ previous sustainable practices}_i + e_{ij}. \tag{3}
\]

In model (3), \(\beta_0\) represents the level of sustainable practices in community j, controlling for the other terms in the model. Following the

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2 Or the difference can be tested by including a main effect of peers (which includes friends and kin) and then an interaction effect of peer by friend: peer_{ii} \times friend_{ii}. The coefficient associated with the second term, peer_{ii} \times friend_{ii}, represents the additional effect of peers who are also friends.
multi-level modeling framework, $\beta_{0j}$ is modeled at the community level (level 2) as a function of the previous community norm:

**Level 2 (community level $j$):**

$$\beta_{0j} = \gamma_{00} + \gamma_{01} \text{ previous sustainable practices}_j + u_{0j},$$  

(4)

where the error terms ($u_{0j}$) are assumed independently distributed, $N(0, \tau_{00})$. The parameter $\gamma_{01}$ then represents the extent to which new sustainable practices are affected by old practices manifesting a community norm. Thus the multi-level model allows one to partially address limitation 2 by extending and testing the boundaries of normative affects. Furthermore, just as in the single level framework, one can adjust (4) for community level characteristics such as size of community, or geographical features.

Importantly, the effect of the norm represented by $\gamma_{01}$ in (4) is not a function of direct interactions or relations. Instead it represents the effect of the general community norm that applies equally to all members of the community regardless of the specific networks in which they are embedded. This contrasts with the network effect associated with $\beta_1$ in which actors with different networks will be affected differently. Therefore, there is great value in comparing the estimates for $\beta_1$ and $\gamma_{01}$ to evaluate whether effects of the general community ($\gamma_{01}$) are stronger than the direct effects ($\beta_1$) of the others with whom a fisherman has an observable social relation such as kinship or friend.

### 8.2.2 The selection of interaction partners

While the influence model represents how actors change behaviors or beliefs in response to others around them, the selection model represents how actors choose with whom to interact. For example, Frank *et al.* (in press) describe how, because of the effects of status and emotional attachment, the provision of help regarding natural resource use is embedded in social networks (Granovetter, 1985). Implied, resources will not flow evenly throughout a social system, but will instead flow differentially depending on the pattern of social relations. For example, the novice lobster fishermen who has marital connections to highliners or who cultivates personal relationships with highliners will be able to access more knowledge than the novice who is new and marginal to a community.
Frank et al. (in press) refer to decisions of to whom to allocate help a "social technology," analogous to the role of production technology. For example, the highliner employs a social technology to determine who to help that yields an expected return in status or conformity to the highliner (Acheson, 1988: 38), just as the highliner employs a fishing technology to extract resources that yields a market return to the highliner. This is clearly borne out in highliners' attempts to deceive specific novices' efforts to discern trap locations, while in other instances a given highliner might share critical fishing knowledge with some novices who are accepted in the community (Acheson, 1988: 103).

Choices such as to whom to allocate resources can be modeled as:

\[
\log \left( \frac{p(\text{help}_{i|j})}{1 - p(\text{help}_{i|j})} \right) = \theta_0 + \theta_1 \text{kin}_{i|j},
\]

where \(p(\text{help}_{i|j})\) represents the probability that actor \(i\) provides help to actor \(j\) and \(\theta_1\) represents the effect of kinship on the provision of help. Other terms could be included such as friendship, members of one's community, etc.

Importantly, (5) can be modified to control for prior tendencies to provide help. This could be done by either modeling only the provision of new help, or by including a term representing whether \(i'\) had helped \(i\) at a previous time point. This addresses pitfalls 1 and 2 by moving past the general association between characteristics of actors and their relations to a more causal statement about a shared characteristic (e.g. kinship) increasing the likelihood of new ties (e.g. help) emerging.

Marijtje Van Duijn (Van Duijn, 1995; Lazega and Van Duijn, 1997) has shown how \(\theta_0\) (the intercept in (5)) can be modeled as a function of characteristics of the provider or the recipient of help, enabling one to test many of the effects specified by Acheson (1988, 2003) and others. For example, \(\theta_0\) can be modeled as a function of the reputation of the recipient of help \((i)\):

\[
\theta_0 = \gamma_{00} + \gamma_{01}\text{reputation}_i + u_i
\]

where the \(u_i\) are normally distributed with variance \(\tau\). A large value of would indicate that those with a positive reputation in the community

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3 I am using the definition of technology as "the application of scientific knowledge for practical purposes" (Oxford English Dictionary, 12th edition). This is different from a common use referring to electronic or mechanical tools.
are able to access more help from others (Acheson, 1988: chapter 2). Similarly, one can model the likelihood of help provided as a function of the seniority of the potential provider of help:

\[ \theta_0 = \gamma_0 + \gamma_1 \text{seniority}_i + v_i \]  
(7)

where the \( v_i \) are normally distributed with variance \( \omega \). A positive value of \( \gamma_1 \) indicates that those with greater seniority are more likely to be named as providing help, as in a highliner effect. Together (5) through (7) define a cross-nested random effects model (estimation of these models is described in the Technical Appendix).

8.3 Application of the models to other chapters in this volume

The models developed in the previous section express the two basic processes of social networks: influence and selection. While the formal modeling framework may feel constraining, the models are quite flexible. To demonstrate their flexibility I apply them to analyses in Bodin and Crona (Chapter 4, this volume). Bodin and Crona seek to identify the characteristics of those actors who occupy specific social positions in their networks. First, drawing on Guimerà and Amaral (2005a, 2005b), Bodin and Crona identify individuals who are hubs of their subgroups, and those who span between subgroups (see also Gould and Fernandez, 1989). This can be represented with a selection model. Let \( \text{CEK}_{i'i'} \) represent whether actor \( i' \) shared ecological knowledge with actor \( i \) and let \( \text{same subgroup}_{i'i'} \) take a value of 1 if actors \( i \) and \( i' \) were assigned to the same subgroup by Guimerà and Amaral’s (2005a, 2005b) algorithm, 0 otherwise. The selection model at level 1 might then be:

Level 1 (Pair \( i,i' \)):

\[ \log \left[ \frac{p(\text{CEK}_{i'i'})}{1 - p(\text{CEK}_{i'i'})} \right] = \theta_0 + \theta_1 \text{same subgroup}_{i'i'} \]  
(8)

The term \( \log \left[ \frac{p(\text{CEK}_{i'i'})}{1 - p(\text{CEK}_{i'i'})} \right] \) is known as the logodds, and transforms the CEK for use in a linear framework. The parameter \( \theta_0 \) represents the log-odds of knowledge being communicated between members of different subgroups and \( \theta_1 \) represents the relative increase in the log-odds for members of the same subgroup; \( \theta_1 \) represents the effect of membership in the same subgroup on the likelihood of knowledge sharing.
Note that model (8) is expressed at the level of the pair of actors. The multi-level framework can then be applied to express effects of either the provider (i) or the recipient of knowledge (j). For example, at the provider level:

Level 2a (Provider of knowledge, i):

\[ \theta_0 = \gamma_{00} + \gamma_{01} \text{ring net}_i + v_i. \] (9)

In this model, \( \gamma_{01} \) represents the extent to which those who use ring nets are more likely to communicate ecological knowledge to others, as hypothesized by Crona and Bodin.

Note that Bodin and Crona’s study is more focused on the type of hub a given actor is, not just whether the actor receives many nominations or not. This could be captured by exploiting the multi-level nature of the selection models. In particular, I can model \( \theta_1 \) from (8) as a function of whether or not the fisher uses ring nets:

Level 2b (Receiver of knowledge, j):

\[ \theta_1 = \gamma_{10} + \gamma_{11} \text{ring net}_j + v_j. \] (10)

Assuming \( \gamma_{01} \) is large and positive, \( \gamma_{11} \) in (10) represents the extent to which a fisherman who uses ring nets is more likely to favor subgroup members vs non subgroup members in his provision of help. A positive value of \( \gamma_{11} \) identifies those who use fisher rings as provincial hubs while a negative value would indicate those who use fisher rings as connector hubs.

If one were instead interested in identifying specific individuals who were provincial or connector hubs one could define (9) and (10) as unconditional models:

\[ \theta_0 = \gamma_{00} + v_i, \] (11)

and

\[ \theta_1 = \gamma_{10} + v_j. \] (12)

Using models (11) and (12), provincial hubs would be defined as those actors who had large values of both \( v_i \) and \( v_j \), indicating individuals who were nominated frequently and especially likely to be nominated by subgroup members. Connector hubs would then be identified as those individuals who had large values of \( v_i \) and small values of \( v_j \), indicating individuals who were nominated frequently but by members of other subgroups.
Bodin and Crona’s study also implies an influence model one could estimate. In particular, in their section on individual characteristics and the potential for agency, Bodin and Crona link the structural pattern of relations to behaviors and knowledge concerning sustainability. These could be modeled directly using an influence model. For example:

\[
\text{Sustainable practices}_i = \beta_0 + \beta_1 \text{exposure to previous sustainable practices of those from whom one obtained ecological knowledge} + \beta_2 \text{previous sustainable practices} + e_i.
\] (13)

Here, \(\beta_1\) indicates the extent to which actors are influenced by those from whom they received ecological knowledge. If Bodin and Crona’s hypothesis “It seems highly unlikely that someone engaged in an illegal fishing practice would coordinate or garner support for new or better fishing regulations and enforcement” is correct, then I would expect \(\beta_1\) to be large and positive, indicating that those who do not engage in sustainable practices induce similar behavior among those with whom they interact.

8.4 Discussion

There are several advantages to the formal models of influence and selection presented here. First, they afford a common framework for communicating theoretical ideas. Any analysis of changes in actors’ behaviors as a function of their interactions can be expressed in an influence model. Any analysis focusing on the pattern of nominations can be translated into a selection model and therefore understood by others studying similar phenomena. These models can also include the effects of other attributes representing different theories or different levels of analysis representing contextual effects (avoiding pitfall 1). Social scientists can then use the models to explore the basis of commonalities across contexts, potentially integrating social science dialog by accommodating effects associated with different disciplines (see Doreian, 2001). Thus a model of how natural resource use is influenced by others can also include effects of social institutions manifest in economic incentives or governmental policies. It can also include biological characteristics of the ecosystem that might constrain or facilitate certain actions.
Second, the models allow specification and testing of specific hypotheses. For example one can test whether there are normative influences of kin, friends, or community members as well as test whether the effects are different from one another. This avoids vague or idiosyncratic descriptions that can emerge from basic storytelling of social network diagrams (pitfall 2).

The influence and selection models also contribute to discourse about the underlying limitations of network data. In specifying the influence model one must consider through which relation resources or norms flow (concerning limitation 1). This is critical for research on natural resource usage which can be influenced through a number of different types of relations. In specifying the selection model one must consider the pools of potential partners including kin, friends, and community members from which an actor makes a selection (concerning limitation 2). In sum, formally specifying network effects ultimately contributes to scientific discourse that is the basis of policy by helping network analysts avoid pitfalls mitigate limitations.

8.4.1 New trends in social network analysis

I have attended carefully to the models of influence and selection because they are the bedrock of social network analysis and because there is an emerging consensus regarding their specification and estimation. But there are important extensions to these models which I outline below.

Dynamics of Social Networks (see special issue of Social Networks, 32(1), 2010). I have presented the models of influence and selection in isolation, when in fact both processes likely occur in most social systems. For example, a fisherman may change his trap placement based on interactions with other fishermen, and then change with whom he interacts based on his new practices. This would apply over long periods to the emergence of new highliners. The dynamic interplay between influence and selection is shown in Figure 8.2. At the top of the waves, influence occurs when actors change their behaviors between two time points as a result of interactions occurring between those two time points. At the bottom of the waves selection occurs when actors change their interactions over one interval (e.g. 0 → 1) to the next (e.g. 1 → 2).

The potential for influence and selection processes can pose a challenge to identifying separate effects and for making causal
inferences. For example, one might infer that actors have influenced one another when in fact they selected similar others with whom to interact. One way to help identify the separate effects is to use longitudinal data to control for actor’s prior attributes. One particular approach to simultaneously estimating models of influence and selection using longitudinal data is Snijders’ SIENA models (e.g. Snijders et al., 2010; Steglich et al., in press). In these models, simulations are used to estimate parameters that will generate the state of the network at time 2, given the state at time 1 and a continuous time conceptualization in which network relations are evaluated for change one at a time.

But the potential for both processes of influence and selection can be treated as a feature as in dynamic models. The advantage of such dynamic representations is they can be used to track how resources flow through a network and generate changes in the network as they do so. For example, consider Sam who receives certain knowledge from Jack (Jack → Sam), but also from Al who talked with Jack (Jack → Al → Sam). An important question then is the effect of the indirect exposure to knowledge (via Al) on Sam in addition to the effect of direct exposure via interacting with Jack. Frank and Fahrbach (1999) posit that indirect exposures represent normative influences as opposed to informational influences of direct interaction; because Sam receives the knowledge directly from Jack, any influence of Al on Sam is likely not knowledge based but instead evidence of Sam conforming to the norm defined by Al’s behavior.
8.4.1.1 Agent-based models via computer simulation

I have grounded the models I presented here in individual behavior and motivations. But it is difficult to extrapolate from them to systemic outcomes, especially those that might be a function of complex feedback. Such systemic implications can be explored using agent-based computer simulations. These simulations are playing an increasingly larger role in the understanding of human–environment interactions (Frank and Fahrbach, 1999; Lim et al., 2002; Parker et al., 2003; Brown et al., 2005). The unique advantage of agent-based modeling comes from being able to simulate the implications of a carefully constructed logic over a series of discrete time steps in order to explore the emergence of macro-level properties from individual-level actions. Critically, the models of influence and selection presented here form a natural basis for the agents’ decision-making rules (e.g. Frank et al., forthcoming). For example, Frank et al. compare diffusion when farmers strategically select who to help based on the potential of the recipient to reciprocate, versus when farmers help those in their local network subgroup who come to them in a time of need. One might initially suspect that when there are only strategic allocations, the “rich will get richer” because allocations will be directed to a select few most able to reciprocate, increasing disparities in access to knowledge. However, Frank et al. find the resource disparity with respect to knowledge decreases dramatically under the scenario where only strategic investments are made. This is partially because more investments are made when people recognize the return on the investment. In turn, more people access the knowledge, reducing knowledge disparities.

Two-Mode Social Networks (see Special Issue of Social Networks: http://www.elsevier.com/framework_products/promis_misc/cfp_socnet_2-mode.pdf). The models I have presented are based on direct social interaction among individuals, but a new trend in social networks is the analysis of two-mode network data, or bipartite graphs. For example, Frank et al. (2008) represented high-school transcript data in terms of clusters of students and the courses they took, as in Figure 8.3. They referred to the clusters as local positions, consisting of a set of students with the courses as focal points of the position. They reasoned that local positions defined pools of potential friends because they attracted students with common interests (represented by the courses); provided opportunities to interact with others (during course participation); and defined a venue in which there were third parties who could enforce norms (the other students in the courses). Frank et al. (2008) then
theorized that because the local positions anticipated the selection process, adolescents could be influenced by the potential friends who were members of their local positions. This is consistent with recent findings and theoretical arguments that adolescents are influenced as much by the peers with whom they would like to be friends as by their current friends who accept them for who they are (Harter and Fischer, 1999; Call and Mortimer, 2001; Haynie, 2001; Giordano, 2003). Frank et al. (2008) found that girls’ math course taking was influenced by the math levels of other girls in their local positions.

The analysis of two mode data has important potential in many social contexts, including that of natural resource users. One can imagine defining local positions of natural resource users based on membership in cooperatives, residence in a community, or participation in certain social events. These local positions might then anticipate the formation of close friendships through which knowledge and normative influence can flow.

Doubtless there are myriad advancements in social networks I have not attended to here. I have not addressed in any depth the contribution of those who study communication (Monge and Contractor, 2003), epidemiology (e.g. Valente, 2002), physics (e.g. Barabasi, 2003; Watts, 2003a,
2003b), or economics (Jackson, 2008). My focus here has been more socio-
logical to examine how natural resource users make decisions in their
social contexts. But interdisciplinary contributions will no doubt be crit-
ic al in the study of natural resource usage. Here I suggest the models of
influence and selection as one way of integrating the contributions from
different disciplines.

### 8.4.2 Implications for managers

The fundamental processes of influence and selection suggest fisheries
managers must account for the dynamic social, economic, ecological,
and cultural conditions of their fishery because the contagion of behav-
iors through a network can affect subsequent network ties, and vice
versa. Therefore, there will be no silver bullets that work across all
contexts (Cochrane et al., in press). Management approaches that rely
largely on markets or property rights may be ineffective, inefficient, or
may produce unintended consequences in certain cultures (Ostrom,
underlying networks such as the gangs of lobster fishermen may not
work in other contexts with a less intact social system, more fragile
natural resource, or unstable political setting, such as the North
American cod fishery or the spiny lobster (Frank et al., 2007).

The basic implication then is for managers to adapt general
practices to local contexts. Classically, managers have needed to
understand the ecology of their natural resources, and how it might
differ from other settings. Managers must be similarly aware of how
the social networks and norms in their communities differ from those
in which practices have been successfully implemented. With greater
understanding of the relationship between social networks and nat-
ural resources usage, managers might ultimately be able to engage in
deliberate action to leverage social networks to change fishing prac-
tices. For example, managers can create venues for interaction such as
hall meetings or informal committees focused on governance.
Managers can also engage social networks by designating individuals
for specific roles. For example, managers in a Vietnamese biostation
in the Mekong Delta have designated members of villages as “local
experts” who work as a liaison between the managers, other villagers,
and other communities in efforts to increase small-scale sustainable
agricultural practices. Thus the managers are locating knowledge in
the social network and strategically modifying specific relations in
the network.
8.5 Conclusion

There is great potential for existing and new social network methods to inform issues of natural resource use. I believe network analysis will be most helpful when it follows the formal modeling framework presented here. It is through this framework that researchers can engage in high-level and direct discourse about the effects of and on social networks. This discourse is critical to understanding the effects of social context on the decisions humans make about how to use precious natural resources.

8.6 Technical Appendix

8.6.1 Estimation of social network models

One’s first inclination to estimate social network models such as in (2) might be to use maximum likelihood techniques such as are available to estimate the parameters in standard logit models (e.g. Agresti, 1984). But it is difficult to define the likelihood for the data given the parameters in model (2) because the observations are not independent. For example, the relation between $i$ and $i'$ is not independent of the relation between $i'$ and $i$.

There are currently two new approaches for accounting for dependencies in social network models such as (2). First, the $p^*$ approach, developed by Frank and Strauss (Frank and Strauss, 1986; Strauss and Ikeda, 1990) and described by Wasserman and Pattison, (1996) shows that estimates from the standard logit model as in (2) can be described as based on a pseudo-likelihood if one conditions on key relations between other pairs in the network. That is, an explicit set of covariates are entered into the model to control for structural dependencies. For example, whether $i'$ informs $i$ might be a function of the number of informants they have in common, the tendency of $i'$ to inform others, etc. In a key point, Strauss and Ikeda argue that a Markov assumption implies that one need only account for relations that involve either $i$ or $i'$ – the “stars” around the actors involved (although this has been extended to account for less direct ties defining neighborhoods; Pattison and Robbins, 2002).

In another estimation alternative, one can account for the nesting of pairs within nominators ($i$) and nominees ($i'$) using an application of multi-level models with cross-nested effects (Lazega and Van Duijn, 1997; Baerveldt et al., forthcoming). These are called $p_2$ models.
because they estimate and control for the variances of actors’ tendencies to send and receive nominations.\textsuperscript{4} One advantage of the $p_2$ approach over $p^*$ is that effects of people can be modeled and tested at a separate level than those of the pair, without attributing most effects to characteristics of the network structure as represented by the $p^*$ covariates. Frank (2009) applied this type of $p_2$ model to estimate the extent to which teachers were more likely to help close colleagues than other members of their schools.

REFERENCES

Baerveldt, C., M. A. J. Van Duijn and D. A. van Hemert (Forthcoming). Ethnic boundaries and personal choice: assessing the influence of individual inclinations to choose intraethnic relationships on pupils networks. Social Networks.

\textsuperscript{4} $p_2$ models can be estimated with the Stocnet software at http://stat.gamma.rug.nl/stocnet/
Social network models for natural resource use and extraction


