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Understanding Peer Influence in Hunter Harvest Decisions Using Social Network Theory and Analysis

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ABSTRACT
State wildlife agencies are increasingly seeking the advice and cooperation of wildlife stakeholders, including that of private hunting cooperatives. While there is some evidence that the interests and actions of private deer cooperatives align with those of state wildlife agencies, little is known about the internal social mechanisms that explain this. Social network theory and analysis can shed some light on these internal group dynamics. This article used egocentric network analysis to examine the effect of peer groups on the antlerless harvest decisions of individuals in private deer cooperatives. Our primary result was that the members of one's egocentric network influence the harvest behavior of that individual, providing some evidence for the potential of social network theory and analysis to understand and improve on the strategies used to address a variety of resource-related problems in wildlife management and conservation.

KEYWORDS
Anterless; cooperatives; deer management; hunting; social network analysis

Introduction

Wildlife in the United States is held in trust by the government for the benefit of the public. State wildlife agencies (SWAs), under the public trust doctrine (PTD), have primary trust responsibilities for non-migratory, non-endangered wildlife (Smith, 2011). However, the importance of engaging a variety of stakeholders in wildlife management and conservation decisions is increasingly recognized because first and foremost, wildlife are mobile, moving across a tapestry of landscapes of varied ownership. Second, 80% of wildlife habitat is found on private lands (Bensen, 2001). Third, an increasing emphasis on ecosystem management implies a need to address natural resource problems at large spatial scales (Grumbine, 1994). Fourth, since the spate of federal environmental laws of the late 1960s and early 1970s, the U.S. Congress has required that government agencies offer opportunities for public input on policy and management (Bean, 1983). Finally, while the PTD implies limiting the influence on decision-making of trust beneficiaries, it is widely accepted that principles of good governance require greater public participation (Decker et al., 2015). Increasingly, SWAs too have sought, whether voluntarily or as a legal requirement, the advice and cooperation

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from wildlife stakeholders to address a myriad of complex, divisive, management problems (Chase, Schusler, & Decker, 2000; Lord & Cheng, 2006).

One such problem is the overabundance of white-tailed deer, which is associated with a variety of human and ecological impacts (Horsley, Stout, & DeCalesta, 2003). Deer densities often exceed state management goals because food abundance is high, winters are increasingly mild, and predator populations have declined (Côté, Rooney, Tremblay, Dussault, & Waller, 2004). Moreover, recreational hunting, as a tool for population control, is constrained by hunters' low demand for antlerless harvest, a decrease in hunter numbers, and declining hunter access (Poudyal, Cho, & Bowker, 2008; Riley et al., 2003; VerCauteren et al., 2011). In Michigan and elsewhere, a strategy widely recognized (Brown et al., 2000; Giles & Findlay, 2004) and commonly employed to address this problem is to encourage the harvest of antlerless deer. For several years, for example, the Michigan Department of Natural Resources (MDNR) has allowed the purchase of 10 antlerless licenses per hunter in some regions and liberal quotas. The MDNR has also authorized the harvest of antlerless deer in and out of season. The problem persists.

There have been few studies examining the correlates of antlerless deer harvest by hunters. Bhandari, Stedman, Luloff, Finley, and Diefenback (2006), an exception, considered hunter sociodemographic and background characteristics as well as hunter field behaviors and motivations to explain antlerless deer harvest. They found that successful doe hunters were typically rural, healthy, spent more time in the field earlier in the season, viewed hunting as a management tool, were motivated by obtaining meat, and were concerned about maintaining access to hunting lands. Hunter age, income, education, experience, and whether they hunted alone or in groups did not explain antlerless harvest success. While helpful, such analytical approaches are grounded in traditional sociological and economic theories; society is comprised of individuals, and it is the attributes of individuals that explain their behaviors. Alternatively, social network theory understands society as composed of social networks, sets of relationships among various actors, and posits that in addition to the attributes of individuals, the relationships with other actors within social networks can help explain individual behaviors such as antlerless harvest.

In this article, we sought to understand the antlerless deer harvest decisions of individuals in private deer cooperatives. Motivated by evidence (Collier & Krementz, 2006) suggesting that private deer cooperatives have had some success aligning hunter behaviors with SWAs' deer management goals, we sought to explain this apparent success. In addition to hunter characteristics, we hypothesized that the behaviors of one's peer groups within private cooperatives influenced individual harvest decisions.

Social networks

Social networks comprise social actors and relational ties between actors. Actors include any social entity such as individuals, organizations, groups, businesses, and governments. Relations are the flow or transfer of material or non-material resources such as information, money, and support. The relational ties between actors in social networks are thought to improve natural resource governance by increasing the generation and sharing of knowledge, mobilizing resources required for effective governance, encouraging cooperation in rule compliance, creating conditions for successful conflict resolution, and

fostering the creation and maintenance of community norms (Bodin & Crona, 2009; Ehrlich & Levin, 2005).

There are two distinct approaches to social network analysis. The first, sociocentric, evaluates the relationships among people of a well-defined group and attempts to understand how the structural patterns of the group explain particular outcomes (see, e.g., Crona & Bodin, 2010). A growing number of studies have used sociocentric analyses to understand the management of common pool resources (Bodin, Crona, & Ernstson, 2006; Bodin & Prell, 2011; Prell, Hubacek, & Reed, 2009).

The second approach, egocentric network analysis, identifies the persons in an individual's network in an effort to understand outcomes related to that individual (Frank, Mueller, Krause, Taylor, & Leonard, 2007). Egocentric analysis can improve our understanding of the variation in social contexts within groups, the relationships between individuals, and the effects those relationships have on individual behaviors and attitudes (Frank & Yasumoto, 1998). While egocentric analyses are more common in other disciplines such as education (Jones, Youngs, & Frank, 2013) and health (Smith & Christakis, 2008), they are still rarely used in the fields of conservation and wildlife management (see one recent example, Stevens, Frank, & Kramer, 2015).

Study site and Southern Michigan deer cooperatives

The deer cooperatives of our study are located in the Southern Lower Peninsula of Michigan, which has the highest density of cooperatives in the state. Of the more than 50 known cooperatives in the southern peninsula, many, including all 15 studied here (Figure 1), follow Quality Deer Management (QDM) strategies to balance the sex ratio and maintain deer densities within habitat limitations by increasing the age structure of bucks and encouraging the harvest of does (Harper, Shaw, Fly, & Beaver, 2013). Deer cooperatives comprise private landowners maintaining full rights to their land while voluntarily cooperating on management and monitoring activities to meet these common management goals. Activities often include sharing knowledge and information, planting appropriate vegetative cover, protecting immature bucks, and harvesting does. Such coordinated activities may affect deer populations and habitat on a larger scale and with greater effect than what would be possible by individuals acting alone.

Methods

Survey methods

We identified potential study cooperatives by first contacting the MDNR and the state office of the Quality Deer Management Association (QDMA), an influential organizing force behind many deer cooperatives in Michigan. We chose our final sample of 15 cooperatives after discussions with cooperative leaders indicating their willingness to participate and coordinate with the researchers on data collection. Such convenience sampling, while usually lower in cost and effort expended, may suffer from bias. For example, by contacting cooperative leaders, it is possible that only the leaders of well-run, successful cooperatives agreed to participate. Had we studied the efficacy of cooperatives or cooperative leaders, this clearly would have been a problem. However, because we were

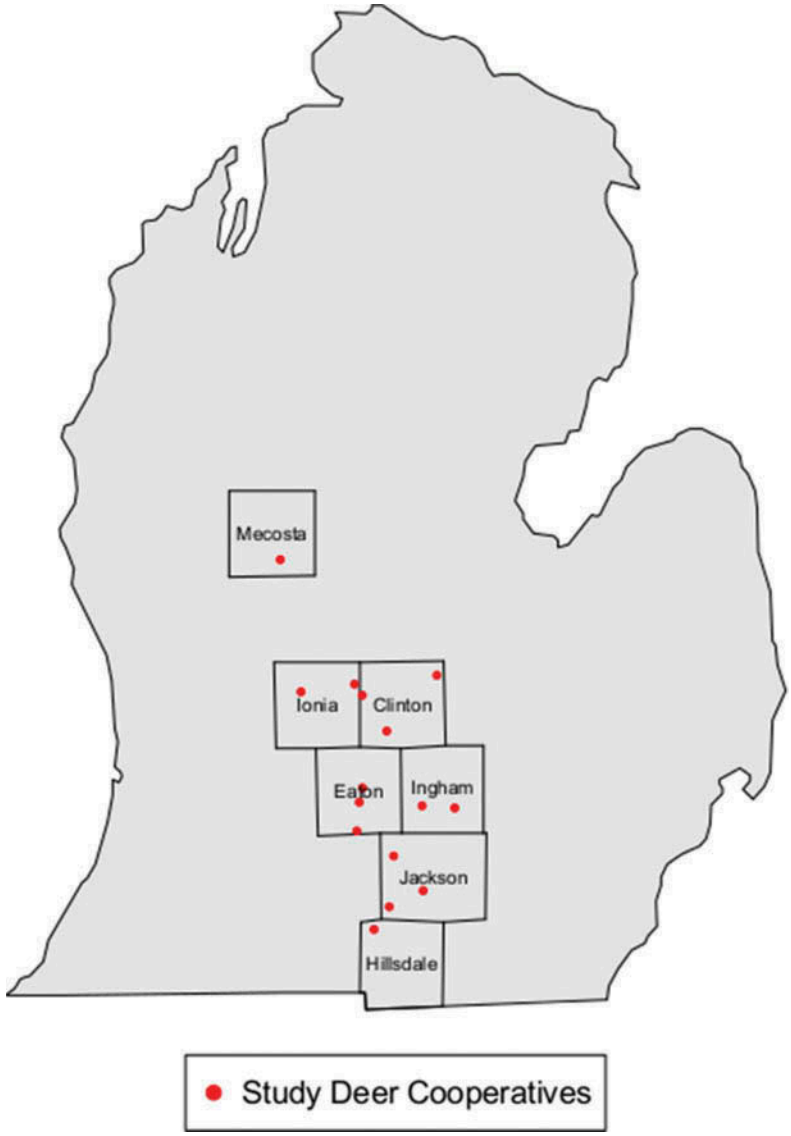

Figure 1. Locations of 15 study deer cooperatives, Southern Michigan, USA.

examining the role of peer influence on member behaviors, while making no judgment as to the goodness of those behaviors, we believe our convenience sampling to be of minimal concern. Still, we acknowledge the potential for bias.

We distributed surveys twice to cooperative members, once in the winter of 2011 (time one) and again in the winter of 2012 (time two). The time one survey consisted of 23 questions regarding demographics, 2010 harvest, harvest standards prior to joining the cooperative, and the egocentric networks of cooperative members. To understand egocentric networks, we asked members (i.e., nominators) to identify other cooperative members (i.e., nominees) belonging to groups representing four dimensions of an individual's hunting network: members with whom they (a) hunted, (b) shared hunting information, (c) shared habitat

management information, and (d) socialized. For simplicity, we refer to these four dimensions later as networks. The time two survey included 35 questions pertaining to 2011 harvest information, habitat management activities, current harvest standards, satisfaction levels, and values. Of the 569 surveys initially distributed at time one, we received 403 responses for a response rate of 71%. Of the 403 time one respondents, 87% also completed the time two survey ($n = 349$), although 45 surveys were eliminated because of missing information, leaving a final sample of 304 respondents.

We used a mix-mode survey distribution method to collect data with approximately 55% of all surveys returned at cooperative meetings, 28% by postal mail, and 17% online. A mixed-mode strategy can exploit the advantages of Internet surveys while minimizing nonresponse bias. Still, researchers must be assured of the equivalency of various survey modes. To assure equivalency, we utilized a unimode design, meaning questions and question wording did not vary across survey modes (Dillman, Smyth, & Christian, 2009). To detect potential mode effects, we compared responses across survey distribution methods using standard statistical methods (i.e., mean comparisons). Finding no significant differences, we feel confident in the equivalency of the three survey distribution methods.

The influence model for doe harvest

Using information on members' egocentric networks, we modeled the effect of peer groups on individual doe harvest behavior. Specifically, our dependent variable is the number of does harvested by each cooperative member in 2011.

After including each of the four networks in preliminary regression models, we determined the socialization egocentric network (i.e., (d) above) as most influential in terms of effect size. The network influence covariate is the mean doe harvest behavior at time one (2010 harvest) of the peers in an individual's egocentric network. For example, assume Allen indicated being socially engaged with three others: Ben, Charlie and Diane. At time one Ben harvested one doe, Charlie three, and Diane two. Allen is then exposed to a mean doe harvest of two (i.e., (1 + 3 + 2)/3 = 2) through his egocentric network. Formally, the exposure of hunter i through egocentric network members i' is:

$$\sum_{i'}(x_{ii'} harvest_{i't-1}) / \sum_{i'} x_{ii'}$$

where the relationship between hunter i and his network relations i' is described as $x_{ii'}$ taking on the value of either 0 (not a network peer) or 1 (a network peer). Thus, the coefficient on the network influence covariate can be understood as the normative influence of others on cooperative member i's harvest behavior (Frank, 2011). For simplicity and owing to little theoretical justification, we did not weight the influence of individual peers, although one could do so based on such proxies as frequency of interaction or survey respondents' own assessment of individual peer influence. Prior antlerless harvest is $harvest_{i't-1}$. The basic influence model is then:

$$harvest_{it} = \beta_0 + \beta_1 \sum_{i'} (x_{ii'} harvest_{i't-1}) / \sum_{i'} x_{ii'} + \beta_2 acres_{it} + \beta_3 age_{it} + \beta_4 buckharvest_{it} + \beta_5 doeharvest_{it-1} + \beta_6 edu_{it} + \beta_7 income_{it} + \beta_8 yearshunt_{it} + \beta_9 yearsmember_{it}$$

where $harvest_{it}$ is time two antlerless harvest of the cooperative member. Other model covariates include acres owned, age, the number of bucks harvested in time two, the number of does harvested in time one, education, income, years of hunting experience, and years as a cooperative member (Table 1). The variable, acres owned, is included as a proxy for opportunity for doe harvest with more acres providing more opportunity. Our observations of cooperative meetings suggested that older members may be less inclined to harvest does, possibly reflecting earlier hunting experiences when deer populations were low, and therefore age is included as a covariate. Bucks harvested in time two may act as a substitute for does harvested in the same year. Education is represented as one of five possible categories (high school; trade school; some college; college; graduate school) as is income ($0–24,999; $25,000–49,999; $50,000–74,999; $75,000–99,999; above $100,000). Years of membership and years hunting may affect harvest behavior as attitudes, values, and knowledge change with experience.

Count data, such as doe harvest, typically follow a Poisson or negative binomial distribution. One approach to modeling is to log-transform the data and fit with a linear model. While some have advocated against this approach as it may lead to bias in the estimated coefficients (O'Hara & Kotze, 2010), others have argued that alternative generalized linear models such as Poisson or negative binomial models, if mis-specified, are prone to higher type-I error rates (Ives, 2015). A key assumption of Poisson models is that the mean and variance of the dependent variable are equal. A violation of this assumption (i.e., over-dispersion) can be addressed with quasi-Poisson or negative binomial regression models. We evaluated the fit and appropriateness of various model specifications using likelihood ratio tests and a test for over-dispersion.

There are concerns about potential dependencies in estimating any social network model (Robins, Snijders, Wang, Handcock, & Pattison, 2007; Steglich, Snijders, &

Table 1. Summary statistics for cooperatives.

Cooperative	Sample size	Year started	Total acres	Mean member acreage	Total doe harvest 2010	Total doe harvest 2011	Mean doe harvest 2010	Mean doe harvest 2011	Mean membership years
123	12	2008	4,900	47.06	19	17	1.19	1.21	3.67
124	18	2009	5,500	105.78	34	19	1.44	1.06	3.06
125	16	1999	9,134	117.02	33	37	1.60	1.85	8.35
126	17	2005	5,000	168.39	39	28	2.16	1.65	5.29
127	47	2006	8,000	58.07	88	60	1.45	1.13	4.08
129	14	2009	5,000	64.18	28	24	1.40	1.14	2.50
130	21	2005	7,500	82.15	55	37	1.84	1.61	6.31
131	26	2009	9,000	151.01	67	42	2.06	1.31	2.83
132	37	2006	2,500	128.49	66	49	1.52	1.19	5.01
133	16	2004	2,500	52.43	27	7	1.30	0.37	6.63
137	11	1997	7,000	488.60	7	3	0.50	0.21	19.77
139	13	2008	5,000	58.32	18	9	0.93	0.64	3.64
140	9	2008	3,500	44.61	21	15	2.10	1.50	3.88
141	35	2010	4,000	123.33	67	43	1.75	1.23	2.14
150	10	2005	5,000	85.92	16	6	1.23	0.60	4.40

Pearson, 2010). In our influence model equation, the estimate on the egocentric influence term is (a) biased if the errors are not independent of the influence term (see Ord, 1975, equations 1.2–1.4) and (b) positively biased if there is some unexplained aspect of harvest behavior that is related to egocentric influence. The most compelling source of such dependencies would be if people choose to interact with others whose behaviors are similar to their own, known as selection in the network literature. Those who tended to harvest a doe at time one might have chosen to interact with similar others between time one and time two and also would have been inclined to harvest a doe at time two. Because the egocentric influence term is likely confounded with prior harvest behavior, our influence model includes a control for prior doe harvest behavior by the individual.

A second concern arises if the model of a hunter's behavior was a function of the contemporaneous behaviors of his/her network members. This would essentially put the outcome on both sides of the model in which case the errors would be directly related to the influence term. To avoid creating dependencies between the errors and predictors by using the same variables on both sides of the model, harvest behavior was modeled as a function of the previous behaviors of others in one's network. We used R, version 3.2.0, for all statistical analyses (R Core Team, 2015). We used KliqueFinder and the R package igraph (Csardi & Nepusz, 2006), to identify cliques within cooperatives and visualize social networks. Kliquefinder identifies cliques by identifying which individuals are more likely to interact with each other than with others in the cooperative by iteratively maximizing the odds ratio of ties between members and their subgroup membership (Frank, 1996).

Results

Total acreage for our study deer cooperatives ranged from roughly 2,500 acres to 9,000 acres (Table 1) with individual ownership ranging from 1 to 1,800 acres and a mean of 74 acres (Table 2). The cooperatives are on average 8 years old with mean membership tenure of 5.4 years (Table 1) and a mean member age of 47 years (Table 2). Compared to deer hunters across Michigan (Frawley, 2012), cooperative hunters harvested relatively more does. Mean doe harvests per hunter in our study cooperatives were 1.5 and 1.1 in years one and two (Table 1). The buck to doe ratio of harvested deer within our study cooperatives over 2 years was 1:2.4 compared to 1:1.0 for all hunters in southern Michigan (Frawley, 2012). Mean doe harvest in year two, our dependent variable, varied among

Table 2. Summary statistics for all cooperative members completing surveys in 2010 and 2011 (N = 302).

	Mean	*SD*	Min.	Max.
Acres owned	112.14	180.77	1	1205
Age	47.19	13.89	18	78
Bucks harvested in 2011	0.52	0.63	0	2
Does harvested in 2010	1.53	1.90	0	17
Does harvested in 2011	1.23	1.56	0	12
Education	3.00	1.32	1	5
Fitness score	4.16	0.79	1.60	5.00
Gender	1.04	0.20	1	2
Income	3.32	1.43	0	5
Network influence (i.e., peer doe harvest)	1.26	1.72	0	8
Years hunted	30.14	13.75	2	62
Years in coop	4.79	4.05	1	35

cooperatives with cooperative 125 having the largest mean doe harvest (1.85) and cooperative 137 the smallest (0.21). We found no qualitative differences in modeling results after fitting our data to linear, Poisson, quasi-Poisson, and negative binomial models. That is, effect sizes and statistical significance of coefficients were similar across model types. Because we have count data and the problems associated with using linear regression with log-transformed data (i.e., presence of zeros in the data set and the interpretation of coefficients beyond reasonable ranges), we considered Poisson or negative binomial regression. We found evidence of over-dispersion in our dependent variable (p = .04). Furthermore, because a Poisson model is nested within the negative binomial model (i.e., the negative binomial model only estimates an additional parameter for dispersion), we compared Poisson and negative binomial models using likelihood ratio tests. As the negative binomial model was a better fit (p = .03), below, we report the results of three model specifications using negative binomial regression.

The influence of peers in one's egocentric network on doe harvest was statistically significant ($p \leq .05$) and positive across all model specifications suggesting a correlation between doe harvest behavior in one's egocentric network and one's own behavior. Across all cooperatives, a one-unit increase in the egocentric influence term (i.e., the mean number of does harvested in one's egocentric network) was associated with a 9% (i.e., e^{β}) increase in the number of does harvested by the individual in time two (Table 3). Other statistically significant variables were doe harvest at time one ($p \leq .01$) and the number of acres owned ($p \leq .05$ or $p \leq .10$ depending on model specification). Doe harvest in the previous year was the strongest predictor of harvest in the next year; harvesting one more doe in 2010 was associated with a 27% increase in doe harvest at time two. Non-significant variables across all models included the number of bucks harvested in 2011, education, income, age, years in cooperative, and years hunting. Comparing the residual deviances of models one and two with a likelihood ratio test, we saw that inclusion of the egocentric influence term significantly (p = .03) decreased the residual deviance. Across all three models, model three, with only the egocentric influence term, prior doe harvest, and a dummy variable for each cooperative (included in all models but not reported in Table 3), was the most parsimonious as evaluated using AIC.

We evaluated egocentric network influence at the cooperative level by interacting the influence covariate with a dummy variable for each cooperative. When comparing cooperatives 125 and 137 for example, the total egocentric network influence effect was roughly

Table 3. Negative binomial regression results with the dependent variable the number of does harvested in 2011 (N = 304).

	Model 1		Model 2		Model 3	
Independent Variable	β	*SE*	*β*	*SE*	*β*	*SE*
Network exposure	0.0840**	0.0382			0.0899**	0.0365
Does harvested in 2010	0.2422***	0.022	0.2433***	0.0223	0.2515***	0.0218
Bucks harvested in 2011	-0.0451	0.1005	-0.0231	0.1012		
Education	-0.0354	0.0526	-0.0203	0.0525		
Income	0.0408	0.0523	0.0475	0.0526		
Age	0.0035	0.0076	0.0013	0.0076		
Acres owned	0.0006*	0.0003	0.0007**	0.0003		
Years in coop	0.0097	0.027	0.0172	0.0268		
Years hunting	-0.0026	0.0075	-0.0019	0.0076		
AIC	849.9		852.6		840.6	

Note. ***p < .01, **p < .05, *p < .1.

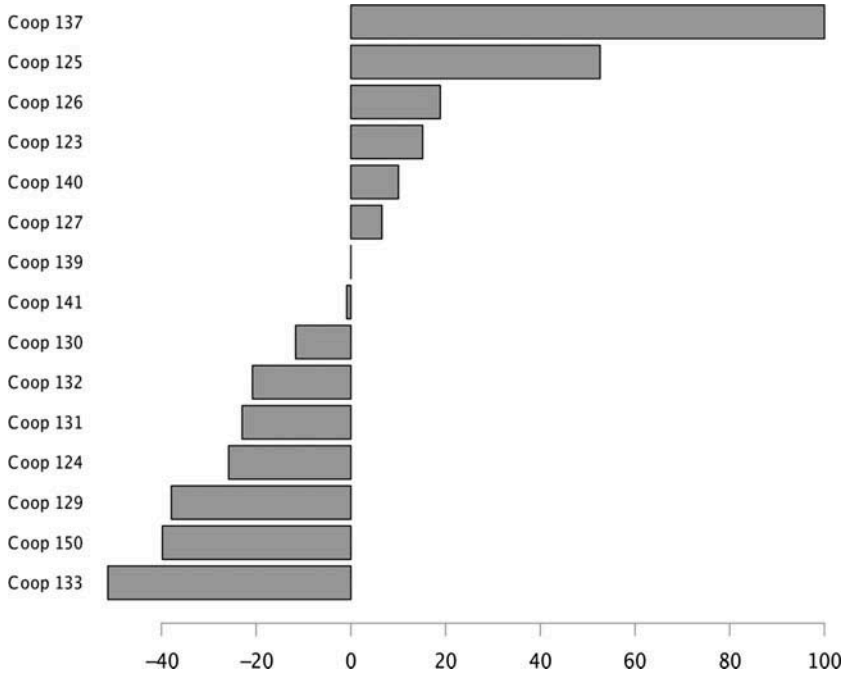

Figure 2. Re-scaled cooperative-specific egocentric network influence coefficients on doe harvest. The coefficients are centered on the cooperative with the median influence value, Coop 139. Egocentric network influence coefficients ranging from -0.704 (Coop 133) to 1.372 (Coop 137) have been rescaled as a percentage of the largest egocentric influence coefficient (Coop 137).

50% greater in 137 than in 125 (Figure 2). Positive, egocentric, influence coefficients indicate that individual behaviors became more similar to those in their network. For example, if nominees harvested many deer in 2010, and the nominator harvested many deer in 2011, the influence would be positive; likewise if the nominees harvested few deer in 2010 as did the nominator. Negative coefficients indicate that individual behaviors became less similar to those in their egocentric network.

Discussion

Across cooperatives, the egocentric network influence model showed that an individual's egocentric network positively affected their harvest behavior. If one's peers were more (or less) likely to harvest does, so was the individual. This result can be validated by the theory of reasoned action, which says that behavior can be predicted by knowing an individual's attitude, the norms he is subjected to, and his intended behavior (Ajzen & Fishbein, 1980). We imitate those we respect, those we find trustworthy, and those whose norms we find acceptable. We found the largest effect size in the social dimension of hunters' egocentric networks, pointing to the important function of socialization in cooperatives. It is also possible that those with whom hunters interact more frequently are more influential, and hunters interact more with those they see socially rather than those with whom they hunt or share information. We can gain additional insight by identifying and visualizing the various cliques within cooperatives.

While the members of cooperative 137 harvested only 10 deer over both years, their egocentric influence effect was the greatest of all cooperatives (Figure 2). Cooperative 137 is the oldest of our study cooperatives and its social network (Figure 3) illustrates 21% connectivity (i.e., the percentage of connections made out of all possible connections) among individuals (arrows express directionality of nominations). While there is some grouping (i.e., different, shaded groups), several members, two of whom are cooperative leaders, bridge the subgroups.

Cooperative 125 showed modest levels of influence (Figure 2). The doe harvest of the 21 members surveyed was 33 in 2010 and 37 in 2011. The network for cooperative 125 (Figure 3) illustrates subgrouping within the cooperative and connectivity of 12%, roughly half that of cooperatives 137. Rather than each individual being connected to each other,

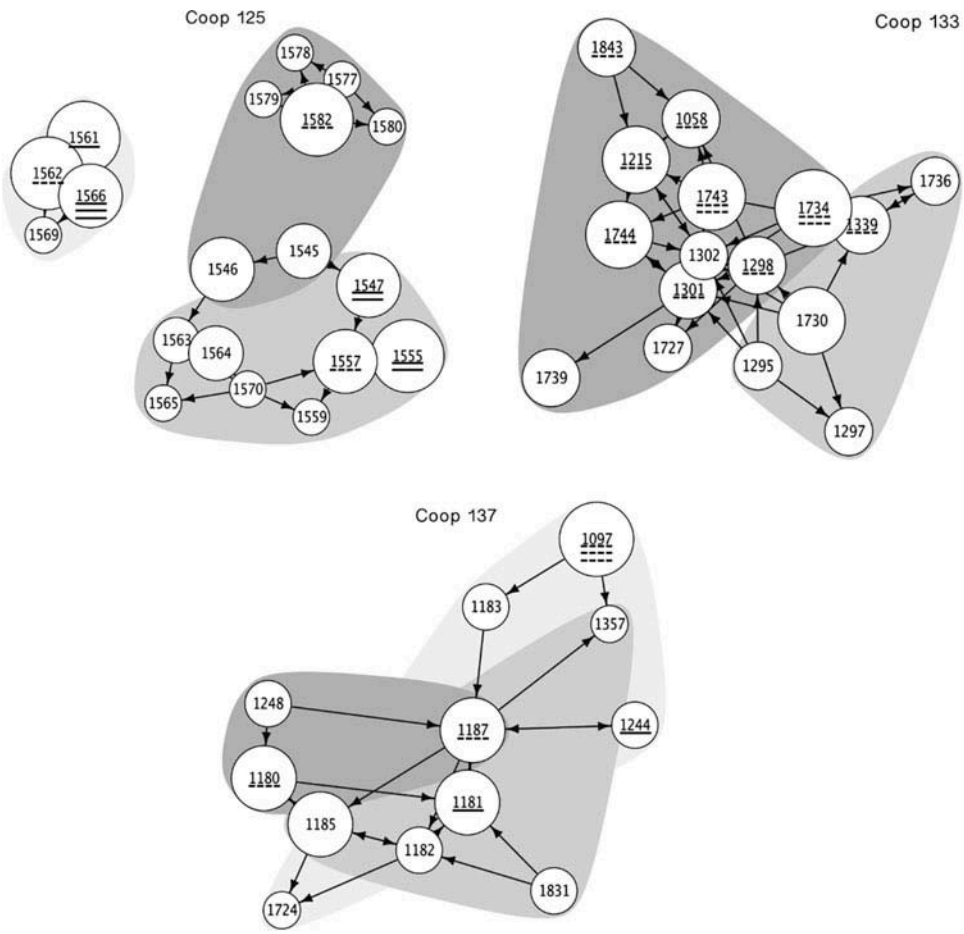

Figure 3. The social interaction network of cooperatives 125, 133, and 137, respectively. The nodes represent individuals; the lines the ties between individuals; and the arrows directionality of nomination. Larger nodes indicate that an individual harvested more does at time one relative to their peers whereas solid (dashed) lines underscoring member IDs indicate more (fewer) does taken in time two than in time one. Individuals without underscoring lines did not change their doe harvest behavior between times one and two. The shading around the nodes is indicative of social groups within the cooperative.

there are three fairly distinct and separate cliques with fewer members bridging the cliques. The cooperative leader, member 1557, received the greatest number of nominations but does act as a bridge between cooperative cliques. However, separation into cliques is consistent with positive influence occurring within the egocentric networks.

Cooperative 133 (Figure 3) displayed the greatest negative egocentric influence (Figure 2). The dark gray clique (Figure 3) consists of older men (mean age 55 years) who farmed together for many years, and the light gray clique consists of younger men (mean age 38 years). Instead of individuals within the cliques influencing each other (as in cooperatives 137 and 125), it is possible that the clique of younger men is influencing the harvest behavior of the older men. Over the 2 years, the young men's clique's mean change in doe harvest was -0.20, while the mean change in harvest for the older men's clique was -1.11. This may indicate that their egocentric interaction networks did not influence members. Rather, the change in harvest in the older men's clique was possibly a result of influence from the younger men's clique, suggesting that a cooperative-level standard is developing and bridging these two groups.

Conclusion

State wildlife managers, using traditional management approaches, have struggled to effectively promote sufficient harvest of antlerless deer to control overabundant populations (Brown et al., 2000; Cote et al., 2004; Giles & Findlay, 2004). We present some evidence that peer influence (i.e., egocentric networks) in deer cooperatives affect individual members' doe harvest behaviors. Generally, this finding is in line with growing evidence that a primary force governing how we behave is how other people behave, particularly our peers. This realization has led to innovative programs addressing smoking, teen drug and alcohol use, AIDS prevention, and economic development (Rosenberg, 2011). Although our study examined private deer cooperatives, our primary result is relevant to any group, private or public, seeking to promote change in wildlife management and conservation; understanding the internal, social dynamics of stakeholder groups is likely important.

For SWAs, policy interventions might be designed to better address cognitive factors related to peer group influences. Information, advice, and assistance could be targeted to influential opinion-makers within groups, increasing the efficiency, efficacy, and dissemination of such interventions. However, if such interventions are perceived negatively, working contrary to their intention, they may do more harm than good within peer groups. Although caution is warranted in projecting our results to the effects on individual behaviors of larger, more broadly defined social media networks, SWAs might explore these effects for opportunities to better educate, inform, and influence. For private groups, clubs, and cooperatives pursuing resource management goals, minding the social aspects of these organizations, peer-to-peer interactions, may be as important as their more formal functions.

As managers, policy makers, and organization leaders are more sensitized to the importance of social networks, their actions and interventions can have broader, positive effects for their constituent communities. Understanding peer influence in egocentric networks may provide a unique understanding of individual behavior change and a more malleable management approach in a myriad of natural resource contexts with largely unexamined and untapped potential for application in resource management and conservation.

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