



Innovation, cooperation, and the structure of three regional sustainable agriculture networks in California

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Abstract

Regional agroecological systems are examples of complex adaptive systems, where sustainability is promoted by social networks that facilitate information sharing, cooperation, and connectivity among specialized components of the system. Much of the existing literature on social capital fails to recognize how networks support multiple social processes. Our paper overcomes this problem by analyzing how the social networks of wine grape growers exhibit structural features related to multiple social processes: ties to central actors that build bridging social capital and facilitate the diffusion of innovations, ties that close triangles and build bonding social capital to solve cooperation dilemmas, and ties to individuals that span community boundaries to connect specialized components of the system. We use survey data to measure the communication networks of growers in three viticulture regions in California. A combination of descriptive statistics, conditional uniform random graph tests, and exponential random graph models provides empirical support for our hypotheses. The findings reflect regional differences in geography and institutional histories, which may influence the capacity to respond to regional environmental change.

Keywords Agriculture · Sustainability · Social network analysis · Exponential random graph models · Complex systems

Introduction

This paper analyzes the structure of social networks among wine grape growers in three regions of CA, USA, that have implemented sustainability partnerships. As with other examples of regional environmental change, wine grape growers make decisions in the context of an agroecological system that must adapt to changing ecological, economic, and social processes. To help growers adapt to these changes, sustainability partnerships aim to build social networks that enable learning, innovation, and cooperation. Our empirical study estimates

the extent to which grower's social networks feature structural configurations associated with these key social processes.

Our analysis contributes to a broad literature that has emerged in the past 20 years across the social sciences, which has established the relevance of social networks among individuals, organizations, and political institutions for responding to regional environmental change (Carlsson 2000; Adger 2003; Weible 2005; Janssen et al. 2006; Bodin and Prell 2011; Barnes et al. 2016). Sometimes referenced under the term “social capital,” social networks are hypothesized to facilitate social processes such as learning and cooperation that enable human societies to adapt to dynamic and complex social-ecological systems (Coleman 1988; Ostrom 1990; Boyd et al. 2011). For example, Doughty (2016) highlights how local policy partnerships can build capacity for resilience by strengthening local networks. Likewise, Dow et al. (2013) describe how bonding, bridging, and linking network activities are used by management planning agencies to facilitate climate adaptation. We build on this work with rigorous statistical tests for specific structural signatures of these forms of social capital across multiple networks.

In the context of agricultural systems, in both developed and developing countries, social networks have been found to be among the most important variables for innovation and

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cooperation (Prokopy et al. 2008; Baumgart-Getz et al. 2012). For example, Conley and Udry (2010) find that farmers in Ghana innovate by mimicking the practices of their successful immediate contacts. Fafchamps and Lund (2003) illustrate how subsistence growers in the Philippines cooperate by informally pooling risk through strong network ties. In California, Hoffman et al. (2015) find that informal, social learning channels are used far more than formal resources to learn about vineyard management practices.

However, this literature faces two major puzzles. First, while most researchers agree networks matter, there is no consensus on how different types of networks affect behavior in different regional contexts (Janssen et al. 2006; Bodin and Crona 2009). Second, researchers often ascribe only a single social process to networks—for example, learning or cooperation—instead of analyzing how networks support multiple social processes that contribute to sustainability and resiliency. For instance, in the face of changing water availability in agroecological systems, agricultural producers must learn about new problems in the short-term (how should I irrigate my crops given current water availability?) and long-term (how much water will be available in the next decade, given drought and climate change?) and self-organize to change behaviors and institutions (how can our community reduce groundwater pumping?). Networks that support multiple social processes are more capable of positively contributing to sustainable and resilient social-ecological systems in the face of environmental change.

This paper addresses the puzzle of multiple social processes by arguing that the observed structures in social networks are signatures of three underlying social processes that motivate interaction in agroecological systems: diffusion of innovation, cooperation, and boundary-spanning. Diffusion of innovation theory hypothesizes that innovation is facilitated by networks that efficiently transmit information. Cooperation is facilitated by networks that allow the development of reputation and trust. Boundary-spanning networks link together specialized components of food systems, which help bring different types of expertise into the overall agricultural value chain.

We test the basic hypotheses emerging from these arguments using surveys of over 500 growers in three different regions to measure their social network relationships. As discussed below, each of these social processes is represented by different structural characteristics of networks, which provides the basis for statistical models that estimate the frequency of different structural motifs that can be thought of as the local building blocks for global network structures. The social processes can be considered generative models for social network structure: Local social processes affect with whom each individual forms ties, and the aggregate of those ties forms structural signatures of the social processes. We also examine the extent to which these structural motifs vary across different regions.

Agroecological systems are important examples of complex social-ecological systems. Globally, agricultural systems have been crucial to the development of modern civilization and they are now facing significant sustainability issues such as food security, natural resource management, and climate change. To address these issues, agricultural systems must catalyze the diffusion of innovations such as new farm management practices (Saltiel et al. 1994; Baumgart-Getz et al. 2012), cooperation to address common-pool resource problems such as groundwater management (Agrawal 2001; Dietz et al. 2002; Henry and Dietz 2011), and boundary-spanning across different specialized components of food systems (Lubell et al. 2014; Hoffman et al. 2015). Viticulture is a particularly useful example because it is a highly innovative and economically viable industry that is increasingly experimenting with sustainability programs, policies, and practices (Warner 2007a; Lubell et al. 2011). While our analysis identifies some of the general processes that we expect are important in agroecology systems, it is also important to consider more comparative research given regional differences in cropping systems, agroecological, and social contexts.

In the next section, we discuss how the social network literature has viewed the relationship between social capital, network structure, innovation, and cooperation. We then describe our hypotheses about how network structures develop in the context of agroecological systems.

Networks: the multiple faces of social capital

A central theme of the environmental change and broader social science literature is that networks constitute a form of social capital that affects the ability of individuals and groups to acquire resources and achieve goals (Coleman 1988; Putnam 1993). Networks are often advocated for enhancing resilience and adaptive capacity in resource management (Adger 2003; Folke et al. 2005; Weible 2005), but it is increasingly recognized that a prescription of “more networks” is insufficient: particular network structures emerge in various situations and are needed for certain capacities (Newman and Dale 2005; Bodin et al. 2006). Network density, for example, may promote trust and compliance with social norms (Granovetter 1985; Coleman 1988), but too much density may lead to homogeneity and reduce capacity for innovation (Oh et al. 2004; Bodin and Norberg 2005). Therefore, in different kinds of decision contexts and over time, we expect to observe different types of social network structures.

The argument that networks support multiple social processes builds on the classic distinction in the social network literature between “open” and “closed” network structures. This distinction appears in a variety of flavors: weak versus strong ties (Granovetter 1973), bridging versus bonding social capital (Putnam 1993; Adger 2003), structural holes versus redundant networks (Burt 2000), and cooperation versus

coordination networks (Berardo and Scholz 2010). Coleman (Coleman 1988) and Granovetter (Granovetter 1985) argue that closure, a network tie between two individuals who share a common partner, is a key aspect of social capital, facilitating cooperation through trust and the ability to sanction non-cooperators. In contrast, Burt (Burt 2000) argues that individuals with links to many other non-redundant groups and individuals—open structures that bridge what he calls “structural holes” between groups—are located in advantageous brokerage positions, with access to diverse sources of information and other resources. Adger (Adger 2003) argues that strong, local bonding ties confer private benefits while bridging or “networking” ties can enhance collective governance. More recently, Berardo and Scholz (Berardo and Scholz 2010) argue that the advantages of open versus closed structures depend on the type of issue at hand. In collective action problems that mainly require coordination, open structures facilitate information transmission by forming ties to central brokers, whereas in more problematic cooperation problems with free-riding incentives, reciprocal and transitive ties that provide closure can enable cooperation.

While the distinction between open and closed networks is useful, we argue that networks may include a mixture of both open and closed structures in order to support multiple social processes. An actor may have some local ties that facilitate cooperation, such as reciprocity or closed triangles. That same actor may also have ties to central actors that serve as information hubs, or to disparate groups that provide novel information or resources. Aggregated to the network level, closed ties create high levels of clustering, while open structures create centralized networks with short-average path lengths that facilitate the rapid diffusion of information. Networks with structures that enable multiple types of social capital contribute to the resilience of complex adaptive systems, which must simultaneously have the capacity to learn and self-organize (Simon 1977; Anderies et al. 2007; Levin et al. 2013). The balance between open and closed network structures is also a feature of the canonical “small-world” network model (Watts and Strogatz 1998).

Linking network structures to key social processes

In this section, we describe the three key social processes that motivate social relationships in agroecological systems, and how they are linked to specific structural properties of networks. Articulating the correspondence between a social process and the network measures that are included in statistical models is necessary to develop hypotheses that can be empirically tested with our wine grape grower data. We test for the structural signature of each social process first by comparing the observed frequency of relevant network statistics to the distribution of statistics in uniform random graphs that make no assumptions about generative social processes, then more

rigorously with exponential random graph models (ERGMs) that control for concomitant effects of multiple social processes.

It is critical to recognize that this empirical strategy does not directly observe the social processes at the individual level, for example the variables affecting an individual’s adoption of an agricultural management practice. Rather, the logic of the argument is that particular types of network structures are more or less likely to occur conditional on the operation of a particular social process. The structural motifs in the network are analogous to the fingerprints of hypothesized social processes.

Innovation, short-path lengths, and centralization

Diffusion of innovation is the classic theory used to describe the process by which individual growers adopt agricultural practices (Ryan and Gross 1943; Rogers 2003). The basic version of diffusion of innovation theory is a variation on rational choice theory, where actors make decisions based on the benefits and costs of a potential innovation. It is assumed that the innovations confer only private costs and benefits at the individual level; the payoff from the adoption decision is independent of the actions of others. Because farmers operate in markets and ecosystems, strict independence is never realized, but it may be a reasonable approximation for some farm-management decisions (Drummond and Goodwin 2010). In this context networks serve primarily to transfer information about the innovation’s benefit/cost ratio and thus can be considered a form of social learning (Lubell et al. 2011; Hoffman et al. 2015).

Diffusion on networks is facilitated by short paths between pairs of nodes (Jackson 2010). At the individual level, rapid access to information is achieved by linking to the center of the network, where information accrues from all parts of the network. At the network level, this generates centralized networks, i.e., networks with high-variance degree distributions. To see why, consider the extremes for a network with N nodes and $N - 1$ edges: If one central node is connected to every other node (i.e., a star graph), the average path length is minimal, $2 \times (1 - \frac{1}{N})$, and degree centralization is maximal. The central node serves as a coordinating hub so that wherever information originates, it is within two edges of every other node. At the other extreme, consider a line graph in which every node is connected to two neighbors (except the two nodes on the ends, which have one neighbor each). This network has maximal average path length, $\frac{N+1}{3}$, and minimal degree centralization. Wherever it arises, information will diffuse slowly. In general, links to central nodes shorten paths and speed diffusion on networks (Leavitt 1951; Peres 2014).

We provide an initial test for this aspect of the networks by comparing observed path lengths and centralizations to those

of uniform random graphs of the same sizes and densities as the observed networks. For each network, we summarize path lengths with the harmonic mean path length (HMPL), which accounts for disconnected dyads (Newman 2003), and centralization with degree centralization, a measure of the absolute difference of degree of each node in the network from the highest-degree node, normalized to the maximum possible value for a network of that size (Freeman 1978). In the ERGM context, we test for network centralization with a geometrically weighted degree (GWD) term, which measures repulsion of edges from high-degree nodes. In networks where access to innovation is a priority of individuals, we expect to see shorter average path lengths and negative GWD estimates (Levy 2016).

Hypothesis 1: HMPLs will be shorter in empirical networks than simulated random graphs, and GWD estimates in ERGMs will be negative, reflecting a tendency for edges to concentrate on popular actors.

Cooperation and triadic closure

In contrast to the classic diffusion of innovation model, there are many agricultural practices for which the payoff is conditional on the actions of others, implying interdependence among growers. For example, pest and disease processes spread over property lines, so if one grower fails to adequately control a disease, the disease prevention efforts of nearby growers will be less effective. Environmental public goods have similar attributes; for instance, one grower's efforts to improve water quality by reducing pollution from irrigation runoff will be ineffective unless other growers in the same watershed also reduce their polluted runoff. These contexts often resemble the strategic structure of a prisoner's dilemma, where cooperation requires overcoming free-riding incentives.

A standard hypothesis within the social capital literature is that closed networks facilitate cooperation by enabling mechanisms of trust and reputation. The classic closed structure is the transitive triangle, where relationships between individuals i - j and i - k facilitate the relationship j - k . These structures help maintain reputation and trust by enabling indirect reciprocity and social sanctions for free-riders and by providing third-party verification of cooperative or uncooperative behavior. In a network where diffusion of innovation is the only important process, the redundant ties in closed triangles would have little value because the information that comes through them is accessible through the shared partner. However, the redundancy of ties that close triangles allows for verification of information, which builds trust, and opens the possibility of social sanctioning, which promotes cooperative behavior (Ostrom 1990; Bodin and Crona 2009; Berardo and Scholz

2010). Hence, closed networks are an important component of community-level social capital thought to enable collective action (Coleman 1988; Putnam 1993).

We test for closed network structures first by comparing observed levels of triadic closure to levels found in uniform random graphs of the same size and density and then via the geometrically weighted edgewise shared partners (GWESP) statistic in ERGMs to test whether there is a tendency for triadic closure above what would be expected by other tie-formation forces in the network (e.g., regional homophily). In networks where cooperation challenges are being navigated, we expect a large number of complete triangles and positive GWESP estimates.

Hypothesis 2: Clustering coefficients will be greater in empirical networks than simulated random graphs, and GWESP estimates in ERGMs will be positive, reflecting a tendency for triadic closure.

Boundary spanning and structural holes

Another important social process in agroecological and other complex adaptive systems is the transfer of information across specialized components of the system. Different components of the system may develop specialized knowledge or capacities, which then must be linked in order to accomplish different tasks. This argument parallels Burt's concept of structural holes, where individuals whose ties span different parts of the system can access more and a greater variety of resources (Burt 2004).

In the context of agriculture, university extension has traditionally filled this role by serving as a bridge between science, policy-makers, and growers. However, this classical model is rapidly being replaced by one of a network of distributed, specialized knowledge, in which both formal outreach professionals and others serve as knowledge brokers (Lubell et al. 2014; Clark et al. 2016b). For example, most cropping systems in California involve certified Pest Control Advisors or Crop Consultants who specialize in specific aspects of agricultural decision-making, and individual growers contract with these specialists to assist the overall farming operation. In other cases, large-scale farming operations create their own in-house expertise. The complex, specialized nature of agricultural knowledge networks challenges the broad stereotype of "one farmer, one farm." Agricultural food systems and innovation systems require sharing of knowledge and coordinated action from many different specialized individuals and organizations (Klerkx et al. 2010; Wigboldus et al. 2016; McCullough and Matson 2016).

Our networks are comprised of growers and outreach professionals and some individuals who fall into both categories. We expect that these "outreach-growers" will play a

boundary-spanning role because they have specialized knowledge, but at the same time, their grower perspective engenders trust from other growers. In network terms, we expect these outreach-growers to occupy positions with high-betweenness centrality; that is, they sit on many shortest paths between other actors in the networks. In ERGMs, we expect the outreach-growers to have more connections.

Hypothesis 3: Outreach-growers will have greater betweenness centrality than growers or outreach professionals, and in ERGMs outreach-grower node-attribute estimates will be positive, reflecting their popularity.

Regional comparisons

The relative prevalence of these different structural motifs may vary across regions, which feature different social and agroecological contexts. For example, our three regions feature considerable geographic differences in their local terroirs, which are administratively recognized as American Viticultural Areas. The concept of terroir refers to a geographically specific constellation of agroecological variables that confer unique character to the local crops. Terroir is especially important for wine grapes because each terroir develops a reputation for a unique flavor and quality of wine, which is reflected in consumer behavior and market price. As a result, wine grape growers have incentives to sub-divide larger AVAs into smaller regions in order to segment the market (Warner 2007b).

The consequences of these regional differences for our networks depend both on physical geography and historical institutional processes. In terms of physical geography, Lodi is a relatively flat and clearly demarcated region in the Central Valley and has only one AVA. Napa features considerably more topographic variation and is subdivided into many small AVAs reflecting the region's long history of wine grape growing and high-value wines. The Central Coast spans a much larger area ranging from Santa Barbara to San Francisco, with disconnected groups of AVAs throughout.

The institutional structure of producer groups and sustainability partnerships also varies across regions. Lodi has by far the most institutionalized producer group, the Lodi Winegrape Commission, which is formally a local special district that spans the entire AVA and even has the authority to tax growers. The Lodi Winegrape Commission developed its own sustainability partnership and third-party certification program called Lodi Rules. On the other hand, both Napa and Central Coast tend to have producer groups associated with specific sub-AVAs rather than a single consolidated organization. The sustainability partnerships in those regions are sponsored by separate organizations who seek to recruit grower participation via cooperation with producer groups.

We argue that the compact geography of Lodi along with its strong institutional arrangements will produce networks that are both more centralized and clustered. The networks in Lodi are thus more effective at spreading information and encouraging cooperation. The Central Coast networks will be the most decentralized and least clustered, with strong homophily at the hyper-local level that does not span across the entire region. The network structures in Napa will fall in between Lodi and Central Coast.

Hypothesis 4: The Lodi network will have the shortest HMPLs, most negative GWD estimates and most positive GWESP estimates. The Central Coast network will have the longest HMPLs, least negative GWD estimates and least positive GWESP estimates. Napa will be intermediate.

Methods

Study system, data, and software

Wine growers and viticulture-outreach professionals in three wine growing regions were extensively surveyed as part of a broader project; complete survey details are available in Hoffman et al. (2014). Briefly, surveys were administered in 2011 for Lodi and 2012 for Napa and Central Coast. Growers were identified from county Agriculture Commissioners' Pesticide Use Reports, and additional eligible growers and outreach professionals were identified through snowball methods. Surveys were issued by mail, and non-respondents were asked several times to respond. The survey response rate was 24% in Central Coast, 39% in Napa, and 45% in Lodi (detailed survey response data are provided in Online Resource 1).

Networks were constructed from survey questions that asked respondents to list up to eight growers and up to eight other individuals with whom they communicate about viticulture management in decreasing order of frequency of communication in Napa and Central Coast and up to four of each in Lodi. To enable comparisons across regions, only the first four individuals listed in each category for Napa and Central Coast were used. Edges are treated as undirected and dichotomous. Additional models, preserving all nominations in Napa and Central Coast, and treating ties as directed, respectively, are presented in Online Resource 1. Isolates were removed from the dataset. Each node in the networks was assigned an attribute type based on whether they are exclusively a grower, exclusively an outreach professional, or both a grower and outreach professional, based on county records and survey question responses. Network data were manually cleaned to merge duplicate entries, correct misspellings, etc. Network

summary statistics and degree distribution plots are presented in Online Resource 1.

All analyses were performed in R version 3.3.3 (R Core Team 2016) using the *statnet* suite of packages, version 2016.4 (Handcock et al. 2008; Handcock and Hunter 2016). All code and data are archived at <https://github.com/michaellevy/ViticultureNetworks-REC>.

Random graph comparisons

For each region, we simulated 1000 random graphs with uniform edge probability and the same size and density as the observed network, constrained to have no isolates, because isolates were removed from the empirical networks. For each region, we compare the empirical value of three graph-level indices of interest to the distribution from the random graphs: normalized degree centralization, harmonic-mean path length (HMPL), and clustering coefficient. If the empirical value is in a tail of the distribution generated by the random graphs, we can infer that some social process has caused the structure of the network to deviate from uniform randomness.

Exponential random graph models

In an ERGM, the network is the outcome variable and the local processes that are hypothesized to generate it, measured as network-level statistics, are the predictor variables. The random graph comparisons described above test one network structure at a time, but it is possible that a single deviation from independence of edge probability drives multiple network-level statistics into the tail of distributions expected under edge independence. For example, a popularity effect will lead to an abundance of closed triangles, even in the absence of a specific triadic closure force (Levy 2016). ERGMs guard against this by estimating parameters on a set of network statistics that jointly maximize the likelihood of generating networks with the observed values of the statistics. Technical details are provided in Online Resource 1.

For each of the three regions, we estimated an ERGM with terms for the GWD and GWESP distribution. For technical details on these statistics and their parameter estimates, see Online Resource 1. In brief, a positive GWD estimate indicates a tendency away from centralization of the network (sometimes called anti-preferential attachment), and a positive GWESP estimate indicates a tendency for triadic closure. We use fixed decay-parameter values of $\theta_S = 3.0$ and $\theta_T = 0.7$.

The models also included main-effect terms for nodal attributes: whether the individual was a grower (baseline category, “Grower”), an outreach professional (“Outreach”), or both (“Outreach-Grower”) and, as a control, whether or not the individual was a survey respondent (“Respondent”). The tendency for actors to link to others who are spatially close was accounted for by including a homophily term for whether the

two individuals in a dyad are in the same zip code. Because we lack information about the location of some individuals, we include two terms: one where we know the two individuals are in the same zip code, and one for which we do not have a zip code for one or both individuals; both are compared to the base case in which the two are known to be in different zip codes. Rather than include a density term in our models, we constrained the number of edges in the candidate graphs to be the same as the empirical networks. This helped circumvent the degeneracy issues that plague ERGMs (Handcock 2003).

Parameter estimates were obtained via Markov chain Monte Carlo (MCMC) maximum likelihood estimation (Hunter et al. 2008; Handcock and Hunter 2016). Details of estimation, MCMC traces, and goodness-of-fit diagnostics are presented in Online Resource 1. In summary, MCMC chains were stationary and well-mixed, and graphs simulated from the models were similar to the empirical networks across a variety of criteria.

Modeled edge probabilities

To better interpret the ERGM parameter estimates, we calculated probabilities of edges conditional on the ERGM estimates. Technical details of this calculation are given in Online Resource 1. We calculated the probability of every possible edge in each of the networks and then parsed the probabilities by nodal and dyadic attributes of interest.

Results

Sociograms of the three wine grower networks are presented in Fig. 1. The Lodi network is the smallest (447 nodes) and most dense (0.0068, fraction of possible ties present), connected (0.84, fraction of dyads with a path between them), and centralized (0.081, normalized sum of deviation of degrees from the most popular actor) of the three, and Central Coast is largest (785 nodes) and least dense (0.0031), connected (0.73), and centralized (0.019), with Napa intermediate on all measures. These differences are all consistent with our regional differences hypothesis, which we subject to more rigorous tests below. Additional descriptive statistics along with degree distribution plots are presented in Online Resource 1.

Outreach professionals and Growers both have relatively low-betweenness centrality, but outreach-growers have high-betweenness centrality in all three networks (Fig. 2, horizontal axis). This is consistent with Hypothesis 3. The vertical axis of Fig. 2 presents the coefficient of variation (σ/μ) in betweenness centrality. While growers have consistently low betweenness and outreach-growers have consistently high betweenness, outreach professionals have more variability in their betweenness centrality: on average, they have low betweenness,

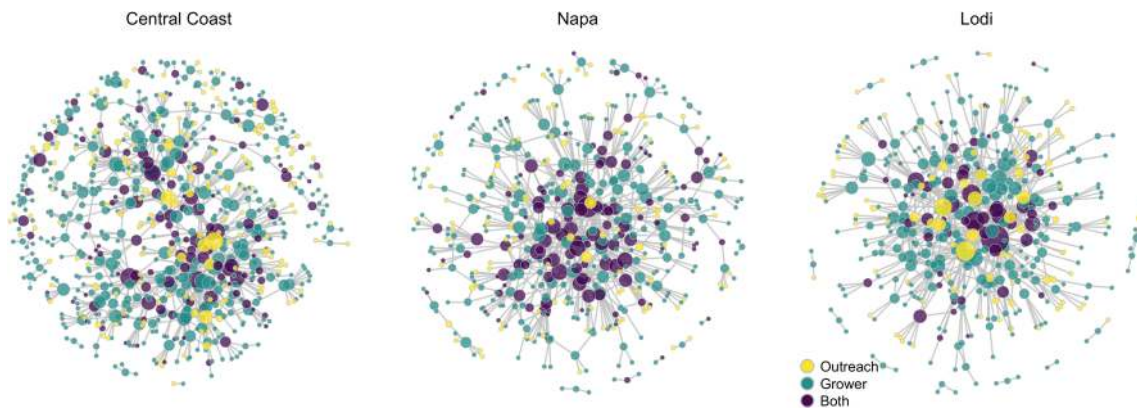


Fig. 1 Viticulture knowledge networks. Sociograms of viticulture management communication in three California wine growing regions. Nodes represent individuals and are colored by professional role and

sized to popularity (node area is proportional to square-root of degree). Graph layouts were generated by the Fruchterman-Reingold algorithm

but there are one or more in each region with very high betweenness, generating large coefficients of variation.

Random graph comparisons

As initial tests of tendencies for triadic closure and popularity effects, we conducted conditional uniform random graph tests that compare the empirically observed clustering coefficients, degree centralizations, and average path lengths to the distribution of the same statistics in 1000 simulated uniform-edge-probability random graphs of the same size and density as the observed networks. The basic intuition of these tests is to generate random graphs that correspond to an assumption of structure unaffected by social processes. If structural configurations representing the hypothesized social processes are present in the empirical networks at a significantly different frequency than in the random graphs, that is an indication of social processes structuring the empirical networks.

Network centralization is greatest in Lodi and least in Central Coast, and in all three regions, the observed level of centralization was greater than in any simulated graph (Fig. 3a). The empirical networks feature a few highly popular actors, more popular than any nodes in the random graphs. In terms of distances between dyads, Central Coast has the longest average path length, and the observed HMPL in Central Coast falls squarely in the middle of the distribution of random graphs ($p(\text{observed} > \text{simulated}) = 0.45$; Fig. 3b). In Napa and Lodi, where the observed path lengths are shorter, all of the simulated graphs had greater HMPLs than the empirical network. These results are consistent with Hypothesis 1, demonstrating the presence of open structures that enable diffusion of information. The results are also consistent with Hypothesis 4: Lodi is the most centralized with the lowest HMPL, while the Central Coast is the least centralized with an HMPL no different from the expectation in a random graph.

The conditional uniform random graph tests demonstrate that the observed networks have far more clustering than expected by chance: no simulated graph in any region has a greater clustering coefficient than the respective observed value (Fig. 3c). These results are consistent with Hypothesis 2. In accordance with Hypothesis 4, Lodi has the greatest clustering coefficient, followed by Napa and Central Coast.

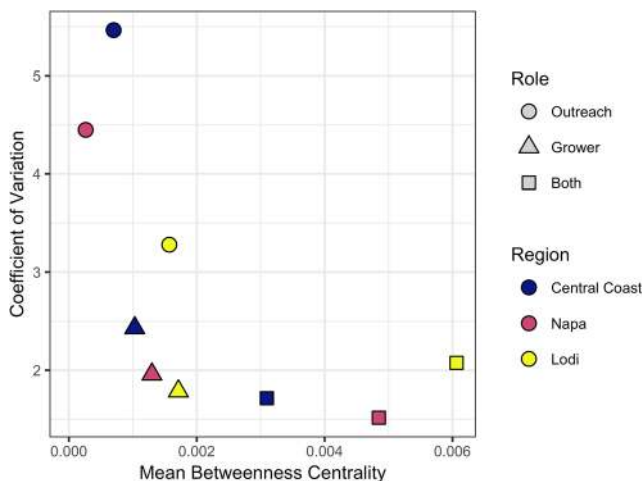


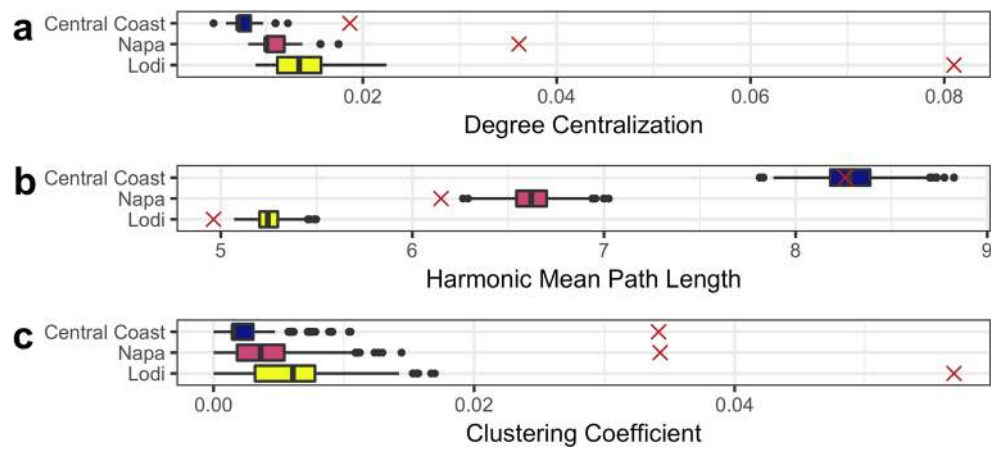
Fig. 2 Betweenness centrality by profession and region. For three professional roles in three wine growing regions, the coefficient of variation (σ/μ) in betweenness centrality versus the average betweenness centrality

Exponential random graph models

The ERGMs test for each social process while controlling for the other social processes, geography, and aspects of the data collection process. Table 1 presents ERGM parameter estimates which, like logistic regression, reflect the increase in the log-odds of a tie for a unit change in the associated statistic.

Consistent with Hypothesis 1, in all three regions, GWD estimates were significantly negative, indicating a tendency for actors to form ties with popular actors. At the aggregate level, this creates centralized networks with short paths

Fig. 3 Simulated random networks (boxplots) versus observed networks (red 'x's) for three graph-level statistics: degree centralization (a), harmonic-mean path length (b), and clustering coefficient (c)



between nodes. The way GWD is formulated makes this effect stronger among lower-degree nodes, but the relatively large θ_s value of 3 gives the statistic significant action over the full range of observed degrees (Levy 2016). For example, in Central Coast, Napa, and Lodi, respectively, the odds of an edge are 8, 9, and 12% greater on a degree-2 node than a degree-1 node, and 5, 6, and 7% greater on a degree-12 node than a degree-11 node. Consistent with Hypothesis 4, this effect is strongest in Lodi and weakest in Central Coast.

Consistent with Hypothesis 2, the positive coefficient estimates on GWESP indicate a strong force for triadic closure in all three regions. Specifically, relative to having no shared partners, the odds of a tie between two people with a single-shared partner are 41, 41, and 49% greater in Central Coast, Napa, and Lodi, respectively.

Additional shared partners make ties even more likely, but the geometric weighting of GWESP implies a diminishing effect for each subsequent partner.

Reflecting the boundary-spanning role posited in Hypothesis 3, in all three regions, outreach-growers have greater tie propensity than growers or outreach professional. All else accounted for, in Napa, outreach professionals are substantially less popular than Growers, while in Lodi, outreach professionals are somewhat more popular than growers. Finally, there is strong regional homophily at the zip code level in all regions, and this effect is strongest in Central Coast, which is consistent with Hypothesis 4. Goodness-of-fit and other model assessments are presented in Online Resource 1.

Table 1 Parameter estimates for ERGMs of viticulture knowledge networks. Outreach, outreach-grower, and respondent are main-effect terms. Geographic terms are homophily effects at the zip code level

| | Central coast | Napa | Lodi |
|---|--------------------|--------------------|--------------------|
| Structural terms | | | |
| Anti-centralization (GWDegree, $\theta_s = 3.0$) | -1.70*** (0.23) | -2.00*** (0.24) | -2.52*** (0.19) |
| Triangles (GWESP, $\theta_T = 0.7$) | 0.34*** (0.07) | 0.35*** (0.07) | 0.40*** (0.06) |
| Professional role (vs. Grower) | | | |
| Outreach | 0.19 (0.15) | -0.84*** (0.20) | 0.22** (0.07) |
| Outreach-grower | 0.31*** (0.05) | 0.37*** (0.06) | 0.23*** (0.05) |
| Geography (vs. known different zip codes) | | | |
| Shared zip code | 1.49*** (0.10) | 0.74*** (0.10) | 0.89*** (0.09) |
| Possibly shared zip code | -0.14 (0.15) | 0.59*** (0.15) | -0.14 (0.13) |
| Control | | | |
| Survey respondent | 1.26*** (0.09) | 1.29*** (0.11) | 0.52*** (0.08) |

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Modeled edge probabilities

To provide intuition on the implications of the ERGM estimates, we calculate the model-implied probability of every possible edge in each of the networks and then parse the probabilities by nodal and dyadic attributes of interest (per Eq. 4). The raw parameter estimates and relative odds presented above speak to the effect of a single feature of the networks independent of all others; in contrast, these edge probabilities simultaneously account for all network statistics associated with a particular edge. For example, if two actors live in the same zip code and have shared partners, the effects of both are reflected in the probability of an edge between them, and correlations between shared zip codes and shared partners will appear in these probability distributions, whereas the ERGM coefficients for shared zip code and shared partners tease apart those two effects.

Figure 4a shows the probabilities of all possible edges versus the degree of edge’s nodes. For example, the left-most box-and-whiskers presents the distribution of probabilities of all possible edges to all degree-1 nodes, the next box-and-whiskers shows the probabilities of possible edges on all degree-2 nodes, etc. In general, there is a positive popularity effect, with edge probabilities increasing with node degree, albeit with decreasing marginal effect. Figure 4b shows the dramatic positive effect of shared partners on tie probability. Across the three networks, actors who share three contacts are an order of magnitude more likely to be

connected than actors with no common contacts. Figure 4c shows that ties involving growers are more likely than ties involving Outreach professionals, and ties involving outreach-growers are substantially more likely still.

Discussion

We analyzed vineyard management networks for structural patterns that support three key social processes for sustainable agroecological systems: diffusion of innovation, cooperation, and boundary-spanning. We find multiple pieces of evidence for all three patterns. Diffusion of innovation is supported by networks with short-path lengths and high levels of centralization, which are evidenced by high-degree centralization and negative-GWD estimates in ERGMs (Table 1) that reflect the tendency for links to go to popular actors. At the same time, we find closed network structures that support cooperation, where individuals are forming closed triangles at levels exceeding chance, leading to networks with high levels of clustering (Fig. 3c) and positive-GWESP estimates in ERGMs. Finally, in each region, there are a few (non-grower) outreach professionals in highly central positions, but many more with only a few connections (Fig. 2). In contrast, outreach professionals who are themselves growers are highly popular and fill structural holes in all three networks. These individuals span boundaries of the networks across groups that would otherwise be poorly connected.

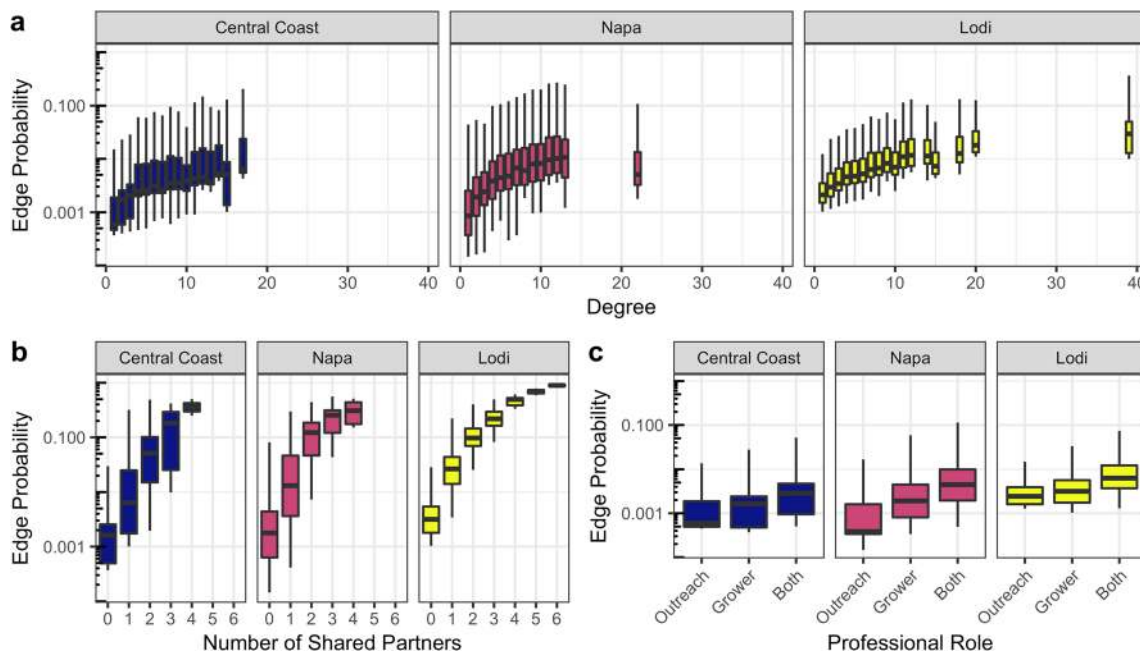


Fig. 4 Edge probabilities implied by exponential random graph models. For each region, the probability of a tie for each dyad in the network was calculated according to Eq. 4. Edge probabilities were then parsed three

ways: degree of the actors (a), number of partners shared by the actors (b), and professional role of the actors (c)

The results also suggest some important differences across regions that reflect the physical geography and institutional arrangements of agroecological systems. These geographic differences reflect the way in which wine grape regions are locally organized around American Viticultural Areas (AVAs), which provide administrative recognition to the terroirs that simultaneously confer unique attributes to local grapes while also fostering a regional identity and sense of community among growers.

Specifically, Lodi has the most homogeneous topography with fewer administrative subdivisions along with a strongly institutionalized grower association and sustainability partnership. As a result, the network is highly centralized, with 5.9 times greater degree centralization (Fig. 3a) and significantly shorter paths between individuals (Fig. 3b) than expected by chance.

In contrast, the Central Coast network has relatively long paths between actors compared to Lodi and Napa, which reflects the fact that the Central Coast is a large geographic region encompassing 11 counties and multiple disconnected AVAs. As a result, 27% of dyads in the Central Coast network have no path between them (the mean among corresponding simulated networks is 11%). At the same time, there is stronger spatial homophily (links between actors in the same zip code) in Central Coast than the other regions (Table 1). In addition, for dyads that are not extremely far from each other in network space (less than ~ 12 edges on the shortest path), empirical paths are substantially shorter than paths in the simulated networks. Thus, information is likely to rapidly diffuse locally in all three regions; it is only across vast network distances that diffusion may be slower in Central Coast.

The inferences this paper can make are limited by survey response rates. Network analysis can be sensitive to missing data; however, we believe it is useful to identify what we can learn from limited data, especially in contexts like agriculture where collecting network data is difficult. Our exponential random graph models partially address this problem by including a parameter that distinguishes survey respondents from non-respondents and demonstrates that survey respondents have more network connections. This finding is consistent with the observation that farmers are more likely to respond to a survey if they are central in the network; the difficulty of reaching more peripheral growers is a consistent theme in agricultural research and policy. Hence, we suspect that including these, more peripheral growers would not add a large number of new links to the data. Additional research (and measurement innovation) is needed to determine the extent to which these unobserved links would shift the relative frequency of open versus closed network structures, which will reflect whether the peripheral growers tend to mention the same central actors or interact in local neighborhoods. Regardless, we do not think the additional data would threaten the validity of our main conclusions

regarding networks having a mix of structures for learning and cooperation.

From a theoretical perspective, the key advancement of this paper is to highlight how social networks support multiple social processes at the same time, not just one of the more traditional models such as diffusion of innovation or cooperation. The ERGMs demonstrate the co-existence of structures that support more than one process, and it is important to note that our models take an epistemological stance of explicitly linking model parameters to hypotheses rather than including parameters just for the purpose of model fit.

From a substantive and policy perspective, our results reinforce the importance of policies and programs that catalyze the multiple functions of agricultural networks. Consider for instance agricultural outreach professionals, who have traditionally been key actors for translating agricultural science into grower behavior. To be effective, agricultural outreach professionals cannot simply broadcast knowledge; they should strategically assemble or “weave” networks (Vance-Borland and Holley 2011; Lubell et al. 2014). Agricultural outreach professionals can develop programs that explicitly intervene in networks, by targeting communication at central leaders or brokers, identifying network subgroups with different communication needs or potential for linkages, or creating new network links for open or closed structures depending on whether the goal is spreading information or fostering cooperation (Valente 2012). Governing institutions like land grant universities or other types of agricultural extension systems should reward outreach professionals for engaging in these types of network-smart strategies (Hoffman et al. 2015).

Clark et al. (p. 4572) echo this point in their discussion of innovation systems, where “reformers have called for and implemented more collaborative, iterative, and interactive models of innovation that acknowledge the importance of co-production relationships between knowledge-making and decision-making. The systemic perspective emphasizes that for success in crafting usable knowledge, researchers must understand the need to work together not only with ultimate users and decision makers, but also with a host of other actors involved in performing the multiple tasks of a well-functioning innovation system: funders, entrepreneurs, field evaluators, etc.” (Clark et al. 2016a). Our results provide direct empirical evidence in support of these conceptual frameworks and policy recommendations.

Agroecological systems are a subset of social-ecological systems, which in turn are a subset of complex adaptive systems. The sustainability and resilience of complex adaptive systems depend on having properties that enable them to learn in the face of uncertainty, self-organize, and link together multiple specialized components of the system. Social networks that encompass these multiple types of processes thus constitute a multiplex conceptualization of social capital. By empirically demonstrating the existence of these different types of

network structures, we hope our study will inspire comparative research across different types of social-ecological systems. Such comparative research will be more valuable if it measures dynamic changes over time, especially how structural properties vary and link to social, environmental, and economic outcomes.

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