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Research

The population ecology of sustainable agriculture knowledge networks: insights from California

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ABSTRACT. Sustainable agricultural knowledge networks consist of heterogeneous actors who collaborate and share knowledge to advance the goals of sustainable agriculture. We analyze how the structure of sustainable agriculture knowledge networks is related to the social-ecological context across 57 counties in California. We apply a population ecology approach that identifies variables related to the space, energy, and stability of the social-ecological context in which networks evolve. Using data from a 2016 survey of agricultural outreach and extension professionals, we find four different types of networks at different stages of development, which vary in the centrality of key actors associated with the University of California. The most highly developed networks exist in agriculturally productive counties with diverse crops. The population ecology variables relate differently to the size versus structure of knowledge networks, which implies a need for ambidextrous extension strategies customized to different types of network processes.

Key Words: *California; social-ecological systems; social networks; sustainable agriculture*

INTRODUCTION

Sustainable agricultural knowledge networks (SAKN) consist of heterogeneous actors who collaborate and share knowledge to advance the goals of sustainable agriculture (Oreszczyn et al. 2010, Cofré-Bravo et al. 2019). SAKN provide a "pluralism of farm advisory services" (Lubell et al. 2014, Dhiab et al. 2020:1) including formal public extension services, agricultural producers' associations, government agencies, non-governmental organizations, consultants, and other types of actors operating at multiple levels of geographic scale. Previous research has shown that SAKN facilitate knowledge transfer (Matous and Todo 2015, 2018), develop social capital (Lubell 2004, Van Rijn et al. 2012; Cofré-Bravo et al. 2019), enable social learning for adaptive decision making (Conley and Udry 2001, Nyantakyi-Frimpong et al. 2019, Schneider et al. 2009), and mediate the relationship between innovators and the institutional environment within innovation systems (Klerkx et al. 2010). A unifying theme in the existing research is how the structure and function of SAKN facilitate the diffusion of agricultural practices.

A question that has received less attention is how do SAKN relate to the social-ecological context from which they emerge? This article addresses this question by adapting Lowery and Gray's (1995) population ecology theory to the case of SAKN in California, USA. The population ecology approach argues that size and structure of populations of organizations depends on the space available for population growth, the energy or resources that will fuel development, and the stability of the underlying environment. Our empirical analysis utilizes a survey of sustainable agriculture actors to measure the size and structure of local networks in 57 of 58 counties in California. Network descriptive statistics are treated as dependent variables in models with predictor variables that operationalize categories from the population ecology theory.

Our application of population ecology is a novel approach to social-ecological systems research. As detailed later, we translate the population ecology concepts into specific measures at the level of counties, which characterizes the social-ecological context in which SAKN emerge. However, the population ecology approach is simpler than other SES frameworks and is less vulnerable to the "exploding variables" problem where the number of social and ecological factors that may be important continues to multiply as studies accumulate. McGinnis and Ostrom (2014) identify 56 "second tier" variables that may affect collective action in SES. Some applications of the SES framework are almost as complex as the reality they purport to describe, which makes it difficult to integrate knowledge (Frey and Cox 2015) or have a common measurement approach (Hinkel et al. 2015). In contrast, the population ecology approach relies on a very simple conceptual framework that in the present case relates SES variables to network size and structure.

Furthermore, a diverse literature calls for a better understanding of networks across different types of SES (Pigford et al. 2018, Bodin et al. 2019, Darnhofer 2020, West et al. 2020). The existing research on SAKN mostly relies on individual quantitative or qualitative case studies (Spielman et al. 2011, Isaac 2012, Isaac et al. 2014, Aguilar-Gallegos et al. 2015, Baird et al. 2016, Cofré-Bravo et al. 2019, Melchior and Newig 2021). The analysis of a single network or case cannot observe how network structure co-varies with the SES context. Analyzing multiple networks provides more opportunities to develop policy recommendations about network management that are customized to different types of contexts, structures, and goals (Provan and Kenis 2008).

Californian agriculture is an excellent case for studying SAKN. With over 69,000 farm operations and almost 10 million hectares of agricultural land, California leads the United States in agricultural value (CDFA 2021). California's Mediterranean climate and diverse geography are suitable for a wide range of crops, with the highest concentration of agricultural production in the Central Valley (consisting of the Sacramento and San Joaquin River basins) and the Central Coast. California's

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agricultural production system is supported by well-developed extension services, notably the University of California Cooperative Extension system with many local county extension agents partnering with university-based researchers and other local organizations. The University of California is a Land Grant University, which was established by the Morrill Act of 1862.

Since at least the early 1990s, accelerating sustainable agricultural production has emerged as an important goal in California (Grieshop and Raj 1992), with many state and local programs promoting practices generally labelled as sustainable, such as conservation tillage (Mitchell et al. 2007), cover crops (Shackelford et al. 2019), and many others purported to support economic, environmental, and social goals. Given the overarching importance of agriculturally productive lands, sustainable and conventional agriculture tend to co-exist in California. Organic or sustainability-certified operations are often proximal to conventional operations and some individual agricultural operations utilize both conventional and sustainable practices. Hence, from a practical standpoint, our study helps understand how knowledge networks support processes of information diffusion and cooperation needed to accelerate the adoption of sustainable practices (Levy and Lubell 2018).

HYPOTHESES

The basic argument of the population ecology perspective is that populations of organizations grow in response to environmental constraints (Lowery and Gray 1995). The population ecology approach considers three sets of variables: space, energy, and stability. Space is the size of the physical area in which populations live, with a larger area expected to support larger populations of individual species and more diverse communities of species. Energy is the stock of resources available to support growth, with more resources expected to increase species density and diversity. Stability is the degree of fluctuation of resource availability, where higher fluctuations are a source of ecological stress and are expected to reduce population density and diversity. All together, these three sets of variables can be conceptualized as a simplified approach to describing a social-ecological context.

We translate these ideas into the context of SAKN. Instead of modeling the size and diversity of an ecological or interest group community, we focus on network size and structure. The logic of the argument is that the contextual variables identified by the population ecology framework establish a niche for networks of different size and structure. Network size is simply the number of nodes in the network. We are interested in four aspects of structure: average degree, modularity, centralization, and the relative centrality of Land Grant University actors. Average degree is a measure of the rate at which actors connect to each other in the network, which is generally expected to increase as the network develops. Modular networks are more likely to feature subgroups and modularity is negatively correlated with more centralized networks where most links go to a single or small core network of actors. As SAKN grow and develop, they become larger, less centralized, more modular and have higher rates of actor connectivity. Because Land Grant University actors have the historical responsibility of spreading agricultural information and knowledge, we expect them to be central nodes in the most developed networks.

For interest group communities, space is the number of potential constituents that can provide political support for interest groups. For SAKN, the most basic measure of space within which SAKN can evolve is defined by the total number of agricultural operations in the county. We expect that a larger number of agricultural operations in an area would attract more demand for active involvement of organizations providing education, extension, and outreach. Also, centralization is generally expected to be lower in larger SAKN networks because leadership is distributed across multiple subgroups rather than being concentrated around a dominant actor in a single group.

Hypothesis 1

In counties with more agricultural operations, SAKN will be larger, more modular, and less centralized and Land Grant University actors will occupy more central positions.

For interest group communities, energy is conceptualized as constituents' interest in specific government goods or services, which then fuels the growth of interest groups advocating for preferred policies. For example, Lowery and Gray (1995) expect environmental threats to catalyze the growth of environmental interest group communities. For SAKN, one source of energy is the overall interest in sustainable agricultural practices. Counties with more organic operations, or operations that implement practices like conservation tillage or cover crops, are indicative of farming communities with more interests in sustainable agriculture. Such practices are often incentivized by government conservation programs, such as the Environmental Quality Incentives Program (EQIP) authorized by the Farm Bill and administered by the U.S. Department of Agriculture.

Hypothesis 2

In counties with higher rates of sustainable agriculture practices and funding, SAKN will be larger, more modular, and less centralized.

The economic structure of agricultural operations and level of public investment in the outreach and extension system are two other potential sources of energy. Larger farms enjoy economies of scale, and farm size is one of the most consistent predictors of innovation adoption (Prokopy et al. 2008). Land Grant Universities like the University of California decide how much to invest at the local level, especially human resources in the form of county extension agents. County extension agents may accelerate the growth of SAKN while also increasing the relative centrality of UC system actors.

Hypothesis 3

In counties with larger farms and more extension agents, SAKN will be larger, more modular, and less centralized and Land Grant University actors will occupy more central positions.

For interest groups, Lowery and Gray (1995) conceptualize stability as the age of the interest group system, which is operationalized by the length of time since statehood. The longer a state has existed, the more opportunities for the growth of the interest group system. For SAKN, we consider two spatial aspects of stability: farm size diversity and crop diversity. Diverse farm and crop systems may produce more ecosystem benefits, provide a portfolio of crops that may be more resilient to market or climate fluctuations, or provide opportunities for mutually beneficial exchanges among inputs and outputs. For example, a large winery may develop contracting relationships with smaller sustainable wine grape producers to produce sustainably certified wine. Or smaller vegetable producers may purchase animal waste from larger producers, for use in compost instead of manufactured fertilizer. These potential opportunities create a niche for the growth of SAKN to identify and support system-level benefits.

Hypothesis 4
In counties with more diverse farm sizes and cropping systems, SAKN will be larger, more modular, and less centralized and Land Grant University actors will occupy more central positions.

METHODS

Here we describe the SAKN survey that was used to identify potential network nodes and edges and the construction of county-level networks. We then explain how we operationalized measures of space, energy, and stability using a variety of archival data sources. The analysis features descriptive network analysis and visualization, as well as basic linear regressions estimating the association between the space, energy, and stability independent variables, with dependent variables as the size, modularity, centralization, and relative position of UC system actors in the SAKN in each county.

Sustainable agriculture survey

The sustainable agriculture survey was fielded from May to July 2016 using Qualtrics online survey software. We defined the sample using a combination of sources, including the University of California Agriculture and Natural Resources (UCANR) employee directory, the County Agricultural Commissioners, County Farm Bureaus, a producer group list from the California Department of Food and Agriculture, participants from eight sustainable agriculture workshops conducted by the lead authors (for details, see Levy et al. 2018), a list of interested stakeholders compiled by the UC Davis Agricultural Sustainability Institute (ASI), and a Google search with the combined search terms "sustainable agriculture" and "county name" for all 58 counties in California. For the Google search, a research assistant selected primary contacts from organizations that appeared to be working on sustainable agriculture issues in each county.

The sample included a total of 2907 potential respondents: 78 from the mental model workshops, 989 from the UCANR list, 142 from producer groups, 346 from the Google search, 53 California Farm Bureau contacts, 59 Agricultural Commissioners, and 1240 from the ASI list. We received a total of 504 completed and 94 partial responses. To minimize the chance of ineligible respondents, the survey included a screening question that asked participants to identify if they worked on sustainable agriculture issues or exit the survey if they did not. Based the proportion of returned surveys where respondents indicated their eligibility, we estimated that 80% of non-respondents were eligible and calculated a response rate of 29% (American Association of Public Opinion Researchers, Response Rate 4). The response rates across groups were as follows: workshop (57%), UCANR list (28%), producer groups (20%), Google search (22%), California Farm Bureau (18%), ASI list (29%), and Agricultural Commissioner (28%).

Although the response rate is reasonable from the perspective of estimating individual-level statistics, missing data is a more significant issue for network data (Kossinets 2006). Hence, we also estimated models (Appendix Table 2) that included as a predictor variable the proportion of zero out-degree nodes in the network, which appeared in the network only as alters and did not contribute any edges themselves. The results of the models including the proportion of zero out-degree nodes were essentially the same, and while not resolving all missing data problems, they did provide one robustness check.

Constructing networks

Because our goal was to analyze variance in the size and structure of SAKN across California's 58 counties, we defined our network boundaries at the county level. Each respondent selected the counties in which they worked from a drop-down list; multiple counties were allowed. Network connections were solicited with the following name generator: "Many different types of individuals and public/private organizations communicate and share information about sustainable agriculture in California. In the spaces below, please list the most important individuals or organizations that you communicate and share information with." We formed an edge list based on the organization of the respondent (ego) and nominated organizational contact (alters). These text entries were resolved at the organizational level for duplicate names (e.g., CDFA = California Department of Food and Agriculture).

Constructing local networks at the county level requires establishing network boundaries, or which nodes and relationships are attributed to a county. The potential candidate network relationships are elicited by the name generator, where a survey respondent "ego" nominates network "alters"; we treated all such ties as undirected relationships. The county-level networks included three basic types of ego-alter pairings: (1) explicit ties where the ego nominates alters who also respond to the survey and indicate working in the county; (2) implicit ties where the ego respondent nominates alters who are not explicitly identified as working in the county (due to survey non-response, item non-response, or indicating working in a different county), and therefore the relationship is implicitly assigned to county via ego's known location; and (3) snowball ties between initial alters who respond to the survey, and then nominate a second-degree alter that is observed exclusively in the county. For example, if ego i nominates alter j (who also responds to survey), and then j nominates k (who does not respond to survey), then k is included in the county-level network if k is not observed elsewhere in the survey via name matching. Limiting the snowball ties to alters not observed elsewhere prevents us from including ties in one county, which may only actually be developed outside the county.

County-level variables

Table 1 summarizes the data sources and calculation of the county-level variables to operationalize the space, energy, and stability concepts described in the theory section. These will be the independent variables in the regression analysis where SAKN size and structure are the dependent variables. Appendix Table 2 summarizes the descriptive statistics for the county-level independent variables, for the four types of networks identified by the cluster analysis below.

Table 1. Description of county-level independent variables.

Variable Names	Construction	Data Sources
Space		
Farm Operations	Total number of agricultural operations in county	2012 Census of Agriculture Quick Stats
Farm Sales	Total value of agricultural sales in county	2012 Census of Agriculture Quick Stats
Agricultural Acres	Total agricultural acres in county	2012 Census of Agriculture Quick Stats
Energy		
Percent Organic Operations	Percentage of agricultural operations that are organic	2007 Census of Agriculture Quick Stats
EQIP Funding per Operation	Amount of EQIP funding in county, divided by total number of farm operations	Environmental Working Group Conservation Database
Conservation Tillage Acres/Harvested Acres	Ratio of conservation tillage acres to acres harvested	2017 Census of Agriculture Quick Stats
Cover Crop Acres/Harvested Acres	Ratio of cover crop acres to acres harvested	2017 Census of Agriculture Quick Stats
Farm Size Index	Weighted sum of midpoint of 12 range class sizes	2012 Census of Agriculture Quick Stats
UCANR County FTE	Number of UCANR full-time FTE assigned to county	University of California Agriculture and Natural Resources
Stability		
Farm Size Diversity	Shannon's Diversity Index based on USDA Agricultural Census farm size classes	2012 Census of Agriculture Quick Stats
Crop Diversity	Shannon's Diversity Index of crop based on spatial analysis	2012 Cropscape Data Layer

Note: Any statistic calculated with number of acres harvested or number of operations in denominator was based on 2012 Agricultural Census data in the denominator, which is sufficient for calculating relative differences across counties but is not an accurate measure for a specific year.
Data Sources: USDA Agricultural Quick Stats: https://www.nass.usda.gov/Quick_Stats/;
Environmental Working Group Conservation Database: https://conservation.ewg.org/index.php;
NASS Cropscape: https://nassgeodata.gmu.edu/CropScape/

Analytical methods

To understand the range of network types across counties, we calculated eight basic descriptive statistics: number of nodes, density (observed ties/possible ties), average degree, average path length, global transitivity (number of triangles/number of triplets), local transitivity (transitivity in local neighborhoods), modularity, and Freeman degree centralization (Wasserman and Faust 1994). Density, average degree, and average path length indicate the overall level of connectivity in the network, while global/local transitivity and modularity indicate the tendency of the network to form subgroups. Centralization measures the similarity of the observed network to the most centralized possible network (a "star" network with all links going to a single node) with the same number of nodes and edges.

In addition to these standard measures of network topology, we analyzed the centrality of nodes associated with the University of California, which as a Land Grant University maintains a system of agricultural outreach and extension services throughout California (UCANR). The UC outreach and extension system consists of both campus-based researchers, and county extension agents working from local offices. We measured the centrality of UC actors by then averaging the degree centrality for all UC-related nodes.

We used cluster analysis to classify the 58 county networks into groups with similar network structures. The cluster analysis first constructs a Euclidean distance matrix based on the eight descriptive statistics of network topology. We used Ward hierarchical clustering to identify four clusters. To better understand the clusters, we visualized the statewide network that includes all nodes, as well as what we viewed as an "archetypal" network from each cluster. We computed the average of the network statistics described above for the four types of networks identified by the cluster analysis below.

We visualized four network diagrams that we considered the best illustration from each cluster. The choice of illustrative network was subjective and qualitative, based on our best professional judgement after visual inspection of all county-level networks. The node sizes were scaled by total-degree centrality, and the high-degree, most central nodes were labeled by their actor type. We also constructed three maps to geographically visualize network structure at the county-level in California: network size or number of nodes, average centrality of UC-system actors, and cluster type. The maps were constructed using the DataWrapper (https://www.datawrapper.de/) online chart and mapping website.

We used linear regression models for more specific hypothesis tests, where the dependent variables at the county level were network size, average degree, average centrality of UC nodes, modularity, and centralization. Network size captures the scale of SAKN in a county, average degree is a measure of connectivity, and the centrality of UC nodes is a measure of the position of a key actor. Modularity and centralization are two global network properties that usually are negatively correlated, where centralized networks tend to have fewer communities (lower modularity) around a core set of central actors, while decentralized networks tend to be polycentric with multiple communities (high modularity) organized around within-community central actors. Because several of the independent variables were highly correlated with each other, and 58 counties represents a relatively small number of observations, we estimated separate models for each category of variable (i.e., space, energy, stability) and then integrated models that retained the strongest predictors.

RESULTS

Table 2 reports the network statistics averaged by cluster, where the most important variables for distinguishing the clusters are number of nodes, local/global transitivity, and the centrality of UC actors. Our labeling of the networks was purely based on our best judgement of how important concepts from the literature relate to observed network structure and our extensive practical experience with SAKN in agricultural systems. Coordinated networks have the largest number of nodes and the highest level of centrality for UC-related actors, who are important coordinators within and between subgroups. Polycentric networks are medium size and distinguished by a high average level of local transitivity with lower modularity, which means that actors are more likely to know each other and link across communities. Fragmented networks are also medium sized but lack the local transitivity of polycentric networks while having a higher modularity, which indicates the existence of more subgroups without common linkages across their boundaries. Connectivity in fragmented networks emerges from more "chain"-like structures where nodes connect in single paths. In contrast, the polycentric networks have more "friends-of-friends" structure that are associated with cooperative self-organization. Emergent networks are the smallest, with a small number of nodes who generally do not know each other.

Table 2. Network statistics by cluster.

	Coordinated (N = 14)	Polycentric (N = 6)	Fragmented (N = 19)	Emergent (N = 18)
Density	0.03	0.09	0.05	0.19
Number of Nodes*	79.00	28.20	38.90	14.80
Average Degree	2.28	2.16	1.91	1.73
Path Length	3.12	2.49	2.93	1.83
Local Transitivity*	0.19	0.34	0.05	0
Global Transitivity*	0.03	0.08	0.01	0
Modularity	0.53	0.45	0.65	0.24
Centralization	0.39	0.41	0.32	0.60
UC Centrality*	7.55	4.03	4.10	4.08

Note: All variables except UC Centrality are descriptive network statistics used in cluster analysis. UC Centrality is the average degree centrality of all nodes associated with University of California, which includes on-campus faculty, on-campus extension specialists, and county extension agents.
* One-way analysis of variance rejects null hypothesis of no significant differences between groups, $p < 0.05$.

Figures 1 through 4 visualize the four types of networks to provide some intuition about the variance in their structural characteristics. The coordinated network in Yolo County (Fig. 1) shows the diversity of nodes and central role of outreach and extension actors like UC Davis and UCANR. At least partly because of physical proximity to UC Davis and the UCANR headquarters, Yolo County has a statewide reputation for innovation and developing university and extension partnerships. The polycentric structure of Yuba County (Fig. 2) in the northern Sacramento Valley shows a smaller network with different types of nodes at the center of multiple communities but connections across communities. UC nodes are important but not always dominant actors in polycentric networks because other types of organizations also occupy central positions. The chain-like structure in Santa Barbara County (Fig. 3) on the Central Coast is typical of fragmented networks, where each central actor has a set of relationships with its own unique community, without much overlap between communities. Emergent networks such as in Calaveras County (Fig. 4) are typically characterized by just a small number of survey respondents, with minimal overlapping relationships.

Fig. 1. Yolo County coordinated network.

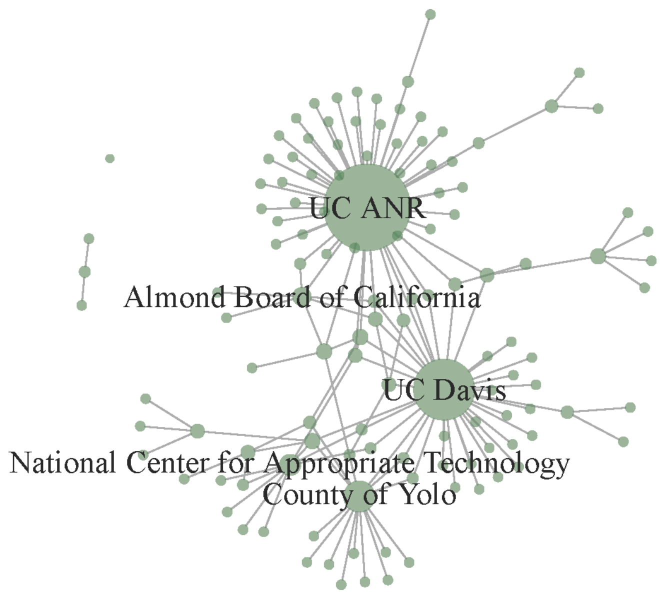
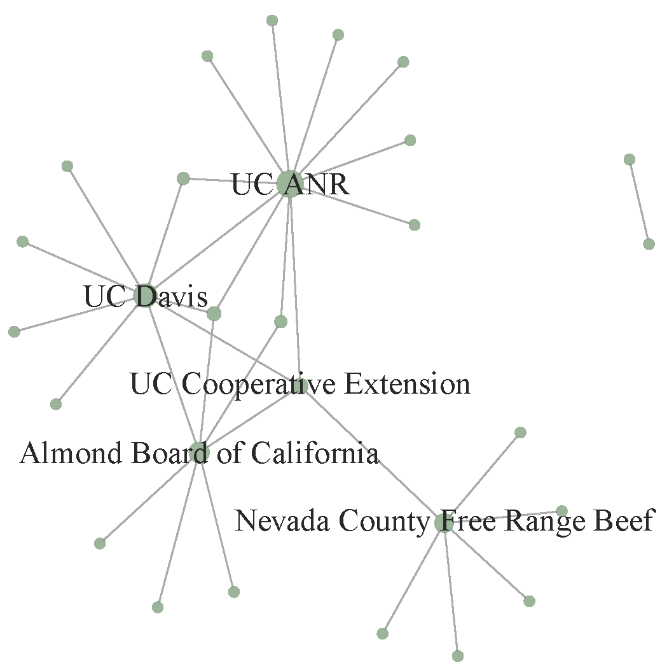


Fig. 2. Yuba County polycentric network.



Figures 5 through 7 displays county-level maps and reveals obvious geographic patterns in the size of the networks (Fig. 5), the centrality of the UC system (Fig. 6), and the type of network from the cluster analysis (Fig. 7). In particular, the largest networks are in California's Central Valley, and represent coordinated networks with a high centrality for UC-system actors. These large, coordinated networks are more concentrated in the Southern San Joaquin valley, which on average has larger

Fig. 3. Santa Barbara County fragmented network.

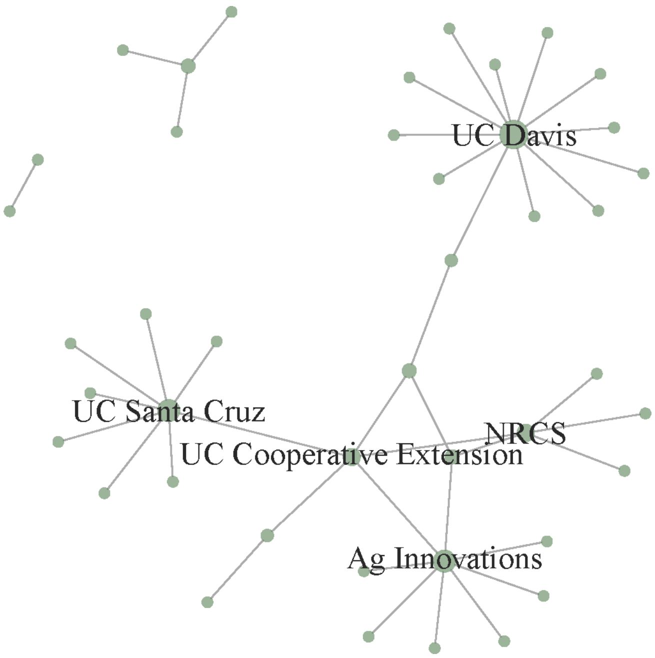
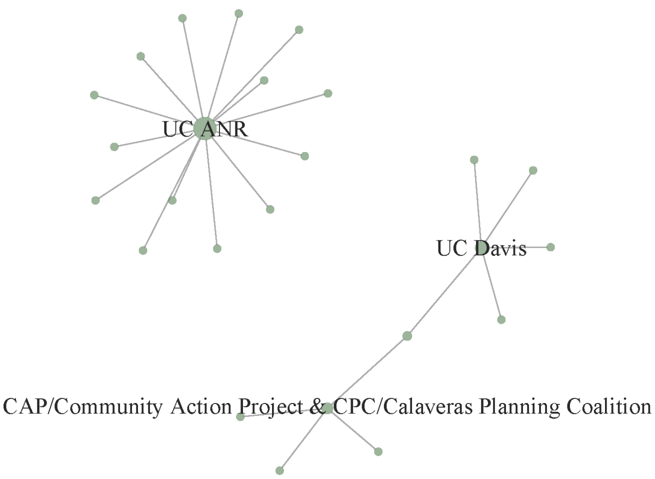


Fig. 4. Calaveras County emergent network.



agricultural operations with high commercial value. The northern Sacramento River Valley contains all the medium-sized, polycentric networks. The Sacramento River Valley has medium-sized operations and a reputation for a more "independent" type of agroecological "culture" than the southern San Joaquin River Valley. The fragmented networks are peripheral to the core Central Valley, in areas that are known for their agricultural economies such at the Central Coast and Napa/Sonoma wine country. The smallest emergent networks are almost entirely in the mountainous areas of California, where there is not a large amount of agricultural production. An interesting exception are

Fig. 5. Size of networks in each county.

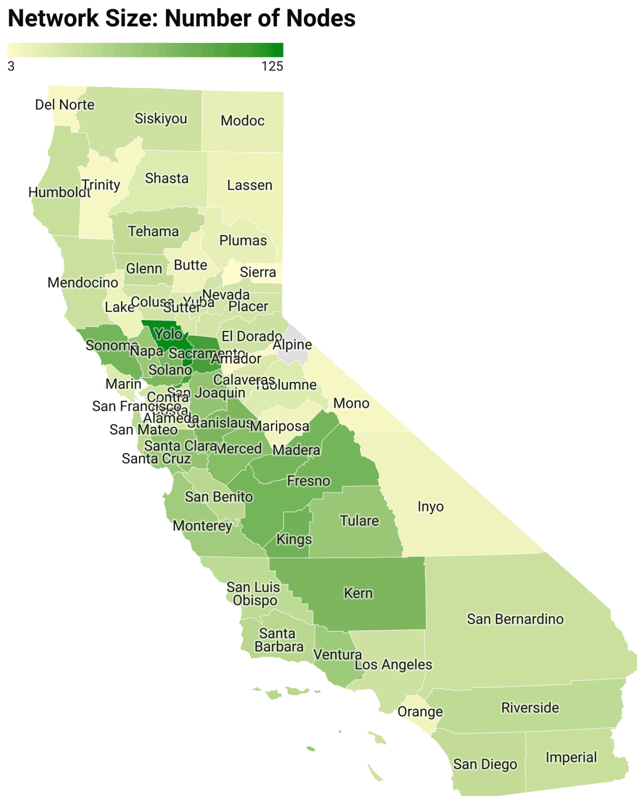


Fig. 6. Average centrality of University of California actors in each county.

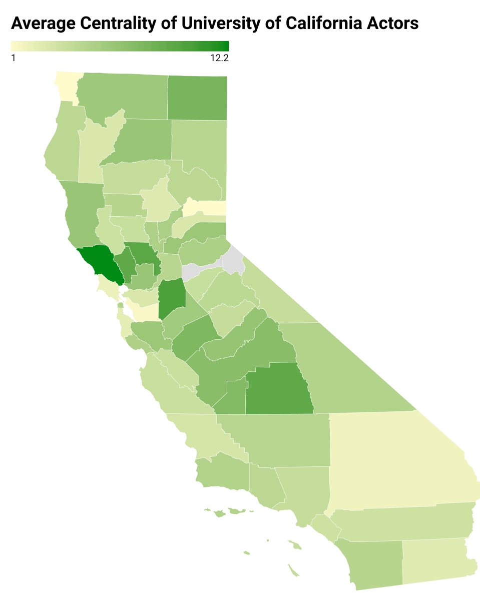
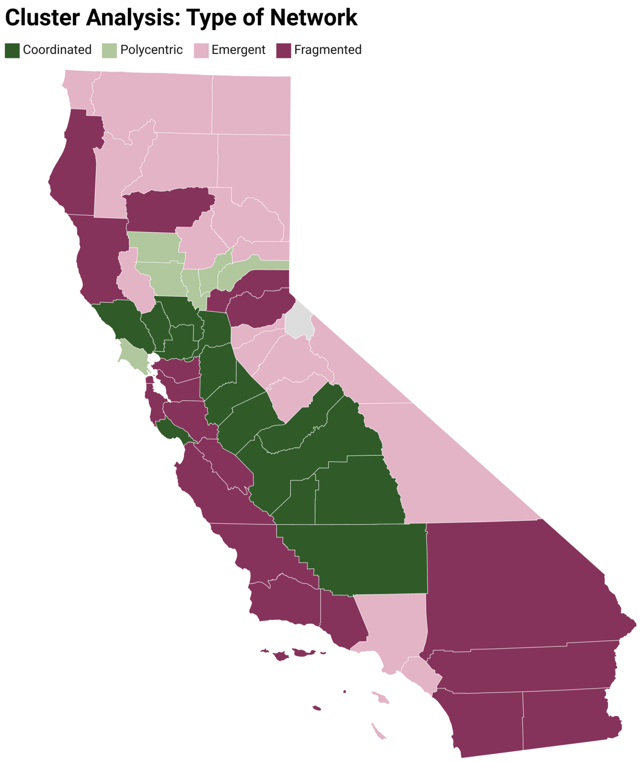


Fig. 7. Type of network in each county.



the emergent networks in the urban Los Angeles region of Southern California, which may be a sign of the need to integrate sustainable agriculture networks into the consumption components of food systems and value chains.

Table 3 presents the results of separate models estimated for each category of independent variables. Because of very high correlations among variables indicating agricultural intensity, the space model only uses the number of crop farms in the county (logged because of skewed distribution). Regarding hypothesis 1, there are strong positive correlations between the number of crop farms and the SAKN size, average degree, and modularity, with UC system actors having a higher average centrality in agriculturally productive counties.

The results for hypothesis 2 imply interesting distinctions for different types of sustainable agricultural practices and funding. On the one hand, counties with more organic operations and higher rates of conservation tillage adoption are more modular and less centralized. This suggests that the adoption of organic agriculture and conservation tillage is occurring in subgroups without strong UC leadership. Conservation tillage may represent a practice that benefits from networks where knowledge is distributed across group members, rather than centralized networks that concentrate knowledge in a core set of actors and may constrain new ways of thinking (Becker et al. 2017, Rulke and Galaskiewicz 2000). In contrast, UC actors are more central in counties with higher rates of cover crop adoption, which is potentially beneficial for a more general range of crop and operation types. Indeed, counties with UC-coordinated networks have the highest rate of cover crop adoption (Appendix 1).

The results for hypothesis 3 support the interpretation that UC leadership is often distributed across subgroups. Higher numbers of full-time equivalent ANR personnel are associated with larger, more modular, and decentralized networks but there is no correlation with the average centrality of UC actors. Combined with the results from hypothesis 1, there is evidence that that the UC is building large networks in agriculturally productive counties with many operations. But these same counties also have a high diversity in types of crops, economic structure of operations, and portfolios of practices. This diversity is associated with subgroup formation, and thus the UC investment appears to be distributing leadership across those subgroups rather than creating centralized networks.

For hypothesis 4, the most important stability variable is the Shannon index of crop diversity, which has a strong positive correlation with SAKN size and weak positive correlation with average degree. The potential for system-level synergies among a diverse portfolio of crops may help form a niche for the growth of networks and stimulate connectivity. There is a weak negative association between the Shannon index of farm size diversity and modularity, which means that counties where farms are more concentrated in one size class tend to have fewer subgroups.

Table 4 reports the pooled regression models that retain the significant predictors from the separate models estimated above. The patterns of association are mostly the same direction and level of statistical significance. The slope coefficients for some independent variables are reduced due to their correlation with the number of crop farms.

DISCUSSION

In this article we analyze the association between SAKN structure and social-ecological context across 57 counties in California through the lens of population ecology, from which we derived hypothesized relationships between context variables and network structure. However, our cross-sectional research design does not capture the co-evolutionary dynamics of SAKN and SES context, so we do not make any empirical claims about causal inference.

Theoretical implications: not only size matters

We argue that the population ecology approach is a useful social-ecological framework for analyzing the size and structure of SAKN. However, we are not arguing that the population ecology approach should generally replace other SES frameworks used in the literature, such as Ostrom (2009). Instead, the population ecology approach is helpful for relating a simple set of social-ecological variables to populations of organizations or types of institutions, which may differentially respond to contextual variables. Such applications require translating the concepts of space, energy, and stability into a specific theoretical or substantive setting.

In the case of SAKN, the population ecology predictor variables show an interesting distinction between network size and structure. The "space" variable of agricultural intensity is mainly associated with network size because SAKN develop in counties with a high level of agricultural activity, where diverse types of crops provide opportunities for system-level synergies.

In contrast, the "energy" and "stability" variables are more related to network structure and reveal a contrast in sustainability practices between cover crops, versus conservation tillage and

Table 3. Separate regression models for each category of variables.

	Estimated Parameters	Number of Nodes	Average Degree	UC Average Centrality	Modularity	Centralization
Space	Intercept	-19.16 (12.25)	1.41 (0.12)*	1.04 (1.13)	0.14 (0.11)	0.53 (0.09)*
	Number of Crop Farms (Log)	9.85 (1.98)*	0.09 (0.02)***	0.65 (0.18)*	0.06 (0.02)*	-0.02 (0.01)
	Adjusted R^2	0.30	0.29	0.18	0.14	0.001
	N	57	57	56	57	57
Energy	Intercept	13.59 (12.93)	1.85 (0.13)*	3.67 (1.24)*	0.20 (0.08)*	0.68 (0.07)*
	Farm Size Index	0.90 (3.23)	-0.02 (0.03)	0.03 (0.30)	-.003 (0.02)	0.02 (0.02)
	Percent of Organic Operations	-0.47 (0.65)	-0.004 (0.06)	-0.13 (0.06)*	.01 (.004)*	-0.01 (0.004)*
	EQIP Funding Per Operation ($1000)	-0.17 (0.30)	0.002 (0.03)	0.02 (0.03)	-.003 (.002)*	0.002 (0.002)
	Ratio Conservation Tillage/Harvested Acres	110.29 (58.32)*	0.35 (0.60)	3.08 (5.57)	1.26 (0.37)*	-0.99 (0.33)*
	Ratio Cover Crops/Harvested Acres	48.30 (42.47)	0.56 (0.44)	11.48 (4.08)*	0.08 (0.27)	-0.07 (0.24)
	ANR FTE 2016-17	6.67 (2.17)*	0.04 (0.02)	0.29 (0.21)	0.05 (0.01)*	-0.04 (0.01)*
	Adjusted R^2	0.23	-0.05	0.12	0.47	0.39
	N	46	46	45	46	46
Stability	Intercept	4.23 (14.64)	1.66 (0.15)*	3.19 (1.38)*	0.62 (0.13)*	0.29 (0.10)*
	Farm Size Shannon's Diversity	2.81 (7.87)	0.08 (0.08)	0.43 (0.74)	-0.15 (0.07)*	0.09 (0.05)
	Crop Type Shannon's Diversity	21.37 (5.56)*	0.11 (0.06)	0.69 (0.53)	0.09 (0.05)	-.02 (0.03)
	Adjusted R^2	0.21	0.07	0.02	0.08	0.01
	N	57	57	56	57	57

Notes: Cell entries are unstandardized regression coefficients with standard errors in parentheses. Separate regression models are estimated for each category of independent variables, which can be seen with separate intercepts and adjusted R^2 values.
* Reject standard null hypothesis of coefficient = 0, $p < 0.05$.

organic agriculture. Conservation tillage is positively associated with the centrality of UC actors, which suggests a more widespread consensus among UC extension professionals. Organic agriculture and conservation tillage are positively associated with modularity and negatively associated with centralization, which suggests these two types of practices are concentrated among smaller communities of practice. County-level investments in the UC system are associated with more modular networks, but not higher average centrality of UC actors, which means that UC leadership is distributed across subgroups of actors that may organize around different approaches to agriculture or cropping systems. This suggests that while some agricultural practices become widespread within innovation system, others persist in smaller niche communities, and they may, or may not, spread more widely across the system over time.

The analysis also highlights the importance of analyzing multiple networks across different areas to better understand the relationships between contextual variables and network structures. We find four types of networks—coordinated, polycentric, fragmented, and emergent—that reflect the history of California agriculture in terms of agricultural productivity, diversity of cropping systems, and levels of investment in extension services and a Land Grant University system. Mapping the geography of SAKN clearly shows how the better-developed networks align with the most important agricultural regions in California such as the Central Valley and Central Coast.

Practical implications: ambidextrous extension strategies

The variance of SAKN across SES context calls for "ambidextrous" extension strategies (Cofré-Bravo et al. 2019), or more broadly "strategic ambidexterity" in agricultural innovation systems (Turner et al. 2017) that exploit the benefits of diverse existing networks while also building new networks to respond to change. Ambidextrous strategies facilitate the development of "best-fit" SAKN that consist of a variety of network configurations ranging from centralized to fragmented, and consequently agricultural innovation systems that align with local social-ecological conditions (Epstein et al. 2015, Klerkx et al. 2017)

Both coordinated and polycentric networks have high levels of modularity that require brokerage across subgroups to discover and capitalize on system-level benefits and mitigate system-level conflicts. In coordinated networks, such brokerage is provided by UC system actors who specialize based on the type of crop (e.g., fruit/nut crops, vegetable crops), input (e.g., pest management), or agricultural strategy (e.g., organic production). Research and outreach that originates in a Land Grant university has a greater chance of spreading in coordinated networks. In polycentric systems, brokerage comes from a wide variety of private, non-governmental, and governmental actors. Effective brokerage requires training these actors to have "relational agency," which is expertise at recognizing and mobilizing the value, knowledge, and skills of other actors (Phillipson et al. 2016). Change agents who build "open networks" that span many "structural holes" across the food system (Burt 2004) are more likely to accelerate innovation, while networks with many overlapping relationships preserve the status quo (Battilana and Casciaro 2012).

In counties with fragmented or emergent SAKN, there may be opportunities to consider different pathways for transitioning to sustainable agriculture as there may be less "lock-in" because of established agricultural innovation system structures (Pigford et al. 2018). The developmental potential of some counties is inherently limited by environmental factors such as water availability, soil fertility, temperature, or other variables. Such limiting factors may shift in the face of climate change, new agricultural technologies, different types of crops like cannabis,

Table 4. Pooled regression models.

	Estimated Parameters	Network Size	Average Degree	UC Average Centrality	Modularity	Centralization
Space	Number of Crop Farms (Log)	9.67 (4.00)*	0.12 (0.04)*	1.26 (0.39)*	0.08 (0.03)*	-0.03 (0.03)
Energy	Percent of Organic Operations	0.69 (0.63)	0.01 (0.01)	-0.03 (0.06)	0.01 (0.005)*	-0.01 (0.004)*
	Ratio Conservation Tillage/Harvested Acres	42.40 (53.24)	-0.28 (0.57)	-0.68 (5.31)	1.27 (0.40)*	-1.00 (0.37)*
	Ratio Cover Crops/Harvested Acres	81.20 (39.83)*	0.61 (0.42)	9.15 (4.03)*	0.04 (0.30)	-0.11 (0.28)
	ANR FTE 2016-17	2.50 (2.24)	-0.02 (0.02)	-0.21 (0.22)	0.04 (0.02)*	-0.03 (0.02)*
Stability	Crop Type Shannon's Diversity	21.69 (7.31)*	0.15 (0.08)*	0.86 (0.73)	-0.04 (0.05)	0.03 (0.05)
Other Model Parameters	Intercept	-74.63 (26.39)*	0.12 (0.04)*	-4.01 (2.58)*	-0.29 (0.20)	0.89 (0.18)*
	Adjusted R^2	0.43	0.18	0.31	0.48	0.32
	N Observations	46	46	45	46	46

Notes: Cell entries are unstandardized regression coefficients with standard errors in parentheses. Each column represents estimates from a single regression model, retaining all important predictors from separate regression models estimated in Table 3.
*Reject standard null hypothesis of coefficient = 0, $p < 0.05$.

or creative food system strategies (e.g., farm-to-fork). The urban counties of California also tend to have less-developed networks, which suggests there are opportunities for building more collaborative and information sharing networks between the consumption and production components of the food system.

Different types of sustainable agricultural practices may require different network management strategies. Our results suggest that conventional cover crops are more widely supported throughout the system and hence undergoing a more traditional "simple" diffusion process. In contrast, organic production and conservation tillage is associated with decentralized networks that tend to form subgroups. The diffusion of more "complex" innovations (e.g., less understood or less locally accepted unconventional practices) may require reinforcement from multiple sources within decentralized network cliques rather than the presence of highly central actors who may not effectively promote change (Centola 2021). Scaling-up these more "alternative" agricultural approaches is perhaps more likely to progress by facilitating communication across pockets of innovative farmers on the peripheries of these networks.

CONCLUSION

Our cross-sectional research design limits us to an exploratory analysis. Additional types of data would help to provide more comprehensive observations of these networks, perhaps through social media or "text as data" approaches (Leifeld 2016, Scott et al. 2020). Untangling the co-evolutionary dynamics requires a long-term research strategy that measures networks over many points in time (Snijders et al. 2010). Longitudinal research at multiple time scales could also help determine how SAKN respond to shocks like climate extreme events, and whether they follow a single developmental trajectory or have potentially multiple trajectories with different equilibrium outcomes.

The present results generate important questions about the role of top-down and bottom-up processes in agricultural innovation systems. Highly central actors like the University of California exert top-down control that may limit system capacity to effectively respond to environmental changes that require new adaptive and transformative practices (Battilana and Casciaro 2012). Such large institutional actors have a long tradition of promoting certain agricultural practices and may preserve the status quo. Subgroups of actors at the periphery of the network experimenting with new agricultural strategies represent a bottom-up process but are likely to have limited system-wide impact without recognition and support from central actors. How these bottom-up and top-down processes cycle and blend over time and hence the strategic ambidexterity of agricultural innovation systems is related to the resilience of the system in the face of change.

Regardless of these limitations and need for future research, the population ecology approach is a useful theoretical starting point to identifying a smaller number of SES variables that are associated with network size and structure to developed more parsimonious, yet theoretically informed, models. The analysis of multiple comparable but highly diverse networks provides the basis for some practical recommendations about agricultural extension, outreach, and transformation strategies that leverage the properties of different network structures and serve as a reminder for caution against generalizing from studies of single or only a small number of networks.

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Data Availability:

The data/code that support the findings of this study are openly available in Dryad at https://doi.org/10.25338/B8ZW6D. Ethical approval for this research study was granted by UC Davis Institutional Review Board project 859413-2.

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Appendix Table 1: Average Values of Independent Variables by Cluster

		Coordinated (N=14)	*Polycentric(N=6)*	*Fragmented (N=19)*	*Emergent (N=18)*
Size	Number of Crop Farms*	1697	568	906	271
Energy	Farm Size Index	2.30	2.51	1.77	3.15
	Percent of Organic Operations	5.59	10.10	9.22	6.51
	EQIP Funding Per Operation ($1000)	16.5	21.7	10.6	31.4
	Ratio Conservation Tillage/Harvested Acres	0.11	0.11	0.11	0.06
	Ratio Cover Crops/Harvested Acres	0.10	0.07	0.08	0.08
	ANR FTE 2016-17	4.00	2.11	3.54	2.02
Stability	Farm Size Shannon's Diversity*	1.96	1.99	1.58	1.83
	Crop Type Shannon's Diversity*	1.88	1.39	1.34	1.21

Note: *One-way analysis of variance rejects null hypothesis of no significant differences between groups, $p<.05$.

Appendix Table 2: Pooled Regression Models Excluding UC ANR FTE and Including Percent Zero-Out Degree Nodes

	Estimated Parameters	Network Size	Average Degree	UC Average Centrality	Modularity	Centralization
Space	Number of Crop Farms (Log)	10.44(3.12)*	0.09(0.03)*	1.01(0.31)*	0.09(0.02)*	-0.03(0.02)
Energy	Percent of Organic Operations	0.74(0.63)	0.003(0.01)	-0.04(0.06)	0.01(0.01)*	-0.01(0.004)*
	Ratio Conservation Tillage/Harvested Acres	41.20(52.11)	-0.22(0.55)	-0.94(5.05)	1.17(0.42)*	-0.96(0.32)*
	Ratio Cover Crops/Harvested Acres	77.36(40.13)*	0.58(0.42)	8.20(4.03)*	-0.005(0.32)	-0.21(0.25)
	ANR FTE 2016-17	NA	NA	NA	NA	NA
Stability	Crop Type Shannon's Diversity	21.68(7.06)*	0.11(0.07)	0.63(0.69)	-0.02(0.06)	0.0003(0.04)
Other Model Parameters	Percent Zero Out-Degree Nodes	-0.07	-0.003	0.08	-0.005	0.02*
	Intercept	-65.66	1.47	-9.04	0.20	-0.95
	Adjusted R^2	0.40	0.17	0.29	0.34	0.43
	N Observations	51	51	50	51	51

Notes: Cell entries are unstandardized regression coefficients with standard errors in parentheses. Each column represents estimates from a single regression model, retaining all important predictors from separate regression models estimated in Table 3. *Reject standard null hypothesis of coefficient=0, p<.05.