AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
http://ageconsearch.umn.edu
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

The potential of Social Network Analysis as a tool for monitoring and evaluation of capacity building interventions

William N. Faulkner[1] and Apollo M. Nkwake[2]
[1]Flux Research, Monitoring and Evaluation: william@fluxrme.com
[2]African Women in Agriculture Research and Development

Abstract

This paper builds on the work of the African Women in Agricultural Research and Development program to demonstrate the potentially crucial role of Social Network Analysis techniques for measuring the effectiveness of women's empowerment programs in African agricultural research and development. Concepts of social capital formation and communities of practice permeate many theories of change which seek empowerment outcomes. Interlaced within these concepts is the abstract notion of relationships between stakeholders, be they human, institutional, or otherwise. Social Network Analysis is a powerful set of methods which permits the integration of data on relationships into conventional statistical techniques. This paper provides a practical introduction to the theory and practice of using Social Network Analysis in concert with other monitoring and evaluation methods to inform decision-making. Throughout the paper, concrete examples from the African Women in Agricultural Research and Development program experience, specifically patterns of professional association membership among fellows, illuminate key concepts, practices, and recommendations.

Keywords: Social network analysis, agricultural research, monitoring and evaluation, mentorship, capacity building, gender

Introduction

Social Network Analysis (SNA) is an underexploited method in the evaluation of capacity-building development programs. In this paper, we will present a summary of the basics of SNA, as well as when and how it is most useful in evaluation; to back our claims, we demonstrate SNA's utility with an example of a capacity-building program operating across 16 African countries: African Women in Agricultural Research and Development (AWARD). AWARD is a fellowship program concentrated on the professional development of African women scientists. The aim of the program is to strengthen the research and leadership skills of African women in agricultural science, empowering them to contribute more effectively to poverty alleviation and food security in sub-Saharan Africa (Box 1).

SNA is particularly well-suited to capacity-building contexts (when compared to other evaluation methods), for two reasons. First, development actors, including funders and program implementers, are increasingly focused on building networks as an effective response to today's complex and interdependent development problems. When compared to hierarchically organized interventions[1], distributed networks can often adapt more flexibly to emerging opportunities and challenges in their environments, and bring together novel combinations of talent and resources to support innovation (Network Impact, 2014).

Second, most quantitative social science research is centered on attributes of study units, with little to no systematic consideration of the relationships and ties between study units (Knoke and Yang, 2008). SNA permits the incorporation of these relationships into quantitative analysis

 DOI: 10.19268/JGAFS.212017.7

methodologies. SNA examines how individuals, groups, and organizations interact with each other, as well as the strengths of connections and associations that link those entities (Wasserman and Faust, 1994; Fowler and Christakis, 2008).

Applications of SNA to international development capacity building are still relatively rare, but existing works point to the enormous potential of the approach. While examining smallholder agricultural innovation in Ethiopia, Spielman *et al*. (2011, p. 210) found that “smallholder innovation networks are central to these systems”, and that different network structures can strongly influence both the pace and path of innovation. Furthermore, the study concludes that “SNA provides useful insights into the inherent characteristics, measurable indicators, and implications of possible means to enhance smallholder innovation networks in Ethiopia” (Spielman *et al*., 2011, p. 210). Wood *et al*. (2014, p. 1) use SNA to show “that farmers deliberate about science in intensive and durable networks that have significant implications for theorizing agricultural innovation”. Finally, a central claim of an evaluation of food security and nutrition advocacy by Dershem and Bokuchava (2016, p. 1) which integrates SNA is that “knowing the current characteristics and structure of these networks will help Oxfam and network members weave more effective and sustainable networks … in the Caucasus region”.

By bringing the influence of relationships to the forefront of analysis, SNA represents an opportunity to propose a paradigmatic change in thinking: in evaluating development interventions, the attributes of the units (e.g. age of a person, size of a country) can have *equal or lesser* influence on outcomes when compared to their relationships with other actors. In our example involving AWARD, the ability of a woman agricultural scientist to wield influence in her organization may depend less on her education, age, or job title, and more on her use of formal or informal relationships.

The first section of the paper outlines a practical overview of what SNA provides as a monitoring and evaluation technique, and how/when it may be applied within the monitoring and evaluation frameworks of capacity-building interventions. The following section demonstrates the claims of these theoretical sections using the empirical example of AWARD’s Retrospective Social Network Analysis Project (hereafter referred to as the ‘Retrospective SNA Project’ or ‘project’), implemented between February and May, 2016.

Theoretical application of SNA to women’s empowerment programs

Network Theory (Graph Theory) is a formalized method designed to study the influence of relationships. While most quantitative methods treat units of analysis as isolated entities, SNA has the essential capacity to account for the characteristics of relationships between entities:

> Most social research continues to rely heavily on measuring and analyzing the attributes of actors as the units of analysis, whether through survey or experimental data collection. Although attributes and relations are conceptually distinct approaches to investigating social behavior, they should not be viewed as mutually exclusive options…A nation’s annual volumes of exports and imports are characteristics of its economy. But the amount of goods and services exchanged between each national dyad represents the structure of trading networks in the global economy…Relations reflect emergent dimensions of complex social systems that cannot be captured by simply summing or averaging its members’ attributes. Structural relations can influence both individual behaviors and systemic performances in ways not reducible to actor characteristics…The strong inference is that exclusively focusing on actor attributes loses many important explanatory insights provided by network perspectives on social behavior (Knoke and Yang, 2008, p. 7-8).

Box 1: Summary of the AWARD Program

Operation: 2008-2017 (ongoing)

Program vision:
Critical advances and innovations in agricultural development for Africa are led and enriched by the contributions of capable, confident, and influential African women; and the agricultural research and development sector demonstrates increasing responsiveness to the needs and contributions of women.

Program goals:
Strengthen the research and leadership skills of African women in agricultural science, empowering them to contribute more effectively to poverty alleviation and food security in sub-Saharan Africa.
Cultivate a pool of African women to be:
a) Effective within Agricultural Research and Development (ARD) institutions supporting agricultural value chains.
b) Effective across a range of research disciplines serving the sector.
c) Responsive to gender issues in the service of women, without excluding men.
d) Technically competent to generate innovations, especially those needed by Africa's smallholder farmers.

Program model:
Individually tailored two-year fellowships.

Previous results from program MONITORING AND EVALUATION:
- 1,158 agricultural scientists (84 percent of them women) participated.
- 300+ institutions inolved.
- 465 fellows – female agricultural scientist from 11 countries* – have earned an AWARD Fellowship.
- Five women from five countries** participated in a pilot project aimed at Francophone Africa.
- 397 scientists have mentored AWARD fellows.

Next phase:
During its next phase, AWARD will help African research institutions grow in their ability to conduct Gender Responsive Agricultural Research and Development (GRARD). AWARD will continue to invest in African women scientists as agents of change; in the Gender in Agribusiness Investments for Africa (GAIA); in programs to strengthen National Agricultural Research (NARS) institutions; and in creating an enabling environment for gender equality in African agriculture, particularly in supporting women's leadership in agriculture.

* Ethiopia, Ghana, Kenya, Liberia, Malawi, Mozambique, Nigeria, Rwanda, Tanzania, Uganda and Zambia
** Cote d'Ivoire, Cameroon, Senegal, Mali and Burkina Faso

SNA is particularly well-suited to the evaluation of capacity-building interventions because of the linkage between the measurement of relationships and the concept of social capital. The fundamental definition of social capital is, in the view of some theorists, the capacity to access desired resources through social relations (Lin, 1999; Burt, 2000; Reynolds, 2007). Additionally, there is evidence that this social capital is positively associated with tangible career outcomes (Seibert, Kraimer and Liden, 2001), because interactions between individuals with different amounts of social capital also fosters the development of other forms of capital (e.g. human capital, etc.) (Aigner, Flora and Hernandez, 2001; Emery and Flora, 2006; Falk and Kilpatrick, 1999).

SNA is based upon data containing two groups of elements, and generally involves a third, as illustrated in Figure 1.

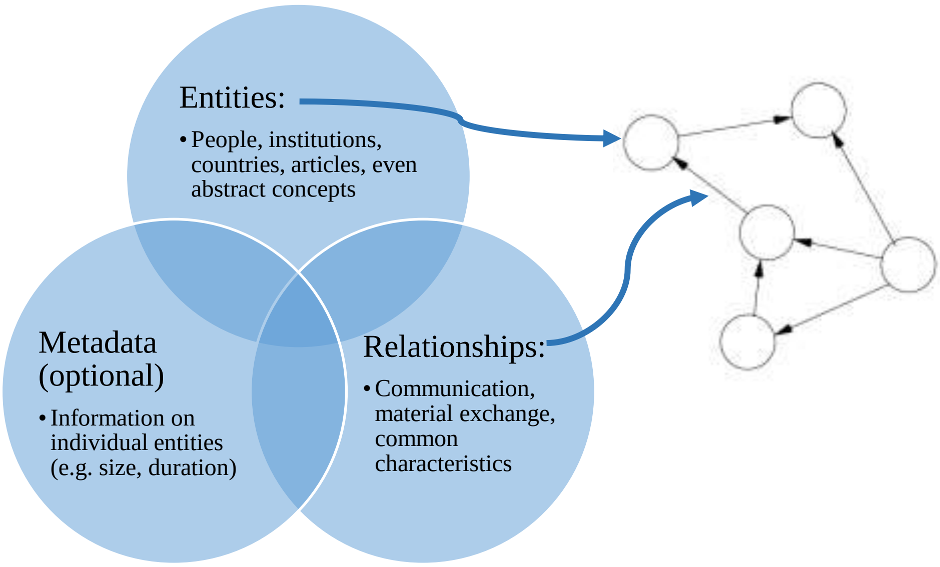

Figure 1: How to build a network

Entities, a.k.a. Nodes, Vertices, and Units of Analysis: while the term "social network analysis" might seem to imply that entities are always human beings[2], in reality they can represent people, institutions, countries, written works, and even abstract concepts.

Relationships, Edges, or Links[3] "Relationship" is also a very general concept; a relationship is any characteristic of interaction which is consistently measurable between all entities. Examples include trust or communication between people, trade between countries, or co-occurrence of keywords in publications. In the most basic sense, the analyst need only be able to confidently assess the existence or non-existence of the relationship.

Metadata (optional): Most network analyses will attach metadata to both entities and relationships. For example, if each entity represents a professional association and a relationship between two associations indicates they share at least one member, useful metadata could include the country location of association headquarters or the number of members.

Results of SNA

SNA usually seeks four types of results:

1. Visualization: mapping; visual inspection to identify areas for deeper analysis.
2. Measures of centrality: showing distribution of "importance" and/or "influence" among

 DOI: 10.19268/JGAFS.212017.7

entities.
3. Structural attributes: understanding type of network; qualifying overall relationship patterns.
4. Subgroup identification: finding sub-groups based on commonalities in structure of relationships.

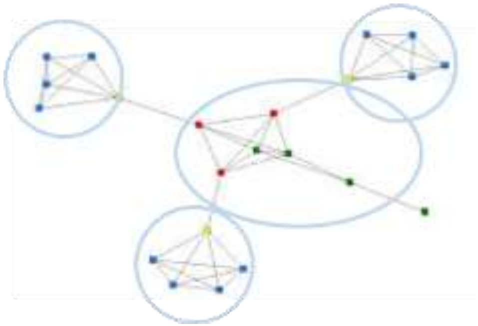

Figure 2: Network graph with subgroups circled

Visualization

Networks can be represented visually as graphs (Figure 2). These visualizations are most useful as "maps" to identify interesting points for further analysis. The two most important tasks for the analyst are therefore to adjust the graph's appearance by choosing a layout algorithm, and adjusting visualization settings. Layout algorithms define the placement and spacing of vertices and edges. These algorithms attempt to create aesthetically appealing, interpretable designs, but there are no objective criteria with which to define any one as superior to another (Hu, 2011). Examples of algorithms include: Fruchterman-Reingold (Fruchterman and Reingold, 1991), and Harel-Koren Multiscale (Koren, Carmel, and Harel, 2002). Visualization settings may be used to manipulate the size, color, shape, and transparency of the different graph elements. Each of these settings can be related to graph data or metadata. For example, the size of vertices representing professional associations might become a linear function of the number of members (the more members, the larger the association node).

Measures of centrality

Most commonly, network datasets are used to calculate measures of centrality, which are different ways of measuring the "importance" or "influence" of a vertex in a network. Usually, an analyst will form the network, calculate some measures of centrality for each entity, and then merge these measures back into the original dataset. These measures then become a new variable in the dataset that can be used in further descriptive analysis or as inputs into a regression.

 DOI: 10.19268/JGAFS.212017.7

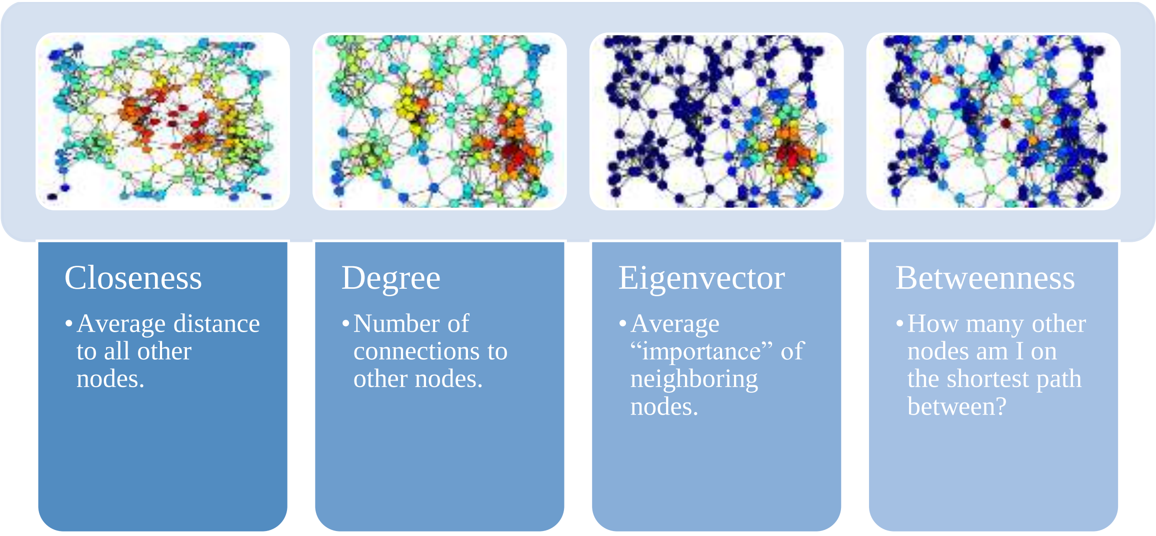

Figure 3: Common measures of centrality

Source: https://en.wikipedia.org/wiki/Centrality

Sub-group identification

Finally, a number of methods exist to define the boundaries of “sub-groups” or “clusters”. A simple technique, for example, is to define “cliques” – sub-groups within which all the entities are connected to one another. In Figure 3, for example, groups B, C, and D are cliques, but A is not. Identifying sub-groups also allows for the identification of entities in certain types of positions. For example, some entities may “bridge” between clusters, while others exist in the center, bonding the other members of the cluster together (Hoppe and Reinelt, 2010). Some analyses may separate out bridging or bonding entities to examine whether they share common traits as an artifact of their positions, despite their distribution in different sub-groups.

Network structure and topology

Some overall properties of networks help the analyst gain a sense of the network’s structure or topology, in the same way that “mountainous” or “rolling plains” might describe some general properties of landscapes. Unlike landscapes, however, network properties are usually only useful when contrasting different networks or sub-groups within a network (comparison using a reference). Some examples of frequently compared properties (in order of increasing complexity):

- Density: the number of connections in the network divided by the total possible number of connections. For a “dense” graph, this measure will be closer to 1, whereas for a `sparse` graph, it will be close to 0.
- Reciprocity: in directed networks, there are 4 possible relationships between any given pair of entities – null (no relationship), A>B, A<B, and A<>B. Reciprocity has several measures, but the most common is to take the number of reciprocated pairs (the fourth relationship type) and divide this number by the total number of connected pairs (any relationship type except null).
- Hierarchy: although intuitively an easy concept, the degree to which a network is hierarchical is difficult to mathematically define. Krackhardt (1994) provides four properties of the perfect hierarchy, against which to compare real-world network structures:
    - Connectedness: nodes and subgroups must not exist on their own.
    - Reciprocity: there must be no reciprocity.
    - Efficiency: only one connection should point towards each node (having

multiple superiors is inefficient).
- Least Upper Bound: every pair of nodes should at some point have one and only one common superior.

Deciding when and how to apply SNA

Despite the generality of SNA as a method, many applications of SNA in monitoring and evaluation systems touch upon only a narrow band of potential applications. Monitoring and evaluation teams can apply SNA to answer a vast array of questions involving diverse types of relationships and overlaps. Limiting the application of these methods to the analysis of relationships between stakeholders, such as information exchange and dissemination among beneficiaries (Hoppe and Reinelt, 2010; Martinez *et al*., 2003; Valente, Gallaher, and Mouttapa, 2004), stops short of utilizing its full potential. Table1 displays an array of examples of other, less common, applications of SNA in monitoring and evaluation.

Table 1: Generalized applications of SNA (non-exhaustive list)

Application Type	Utilization & Examples
Co-occurrence in surveys	Utilization: reveal deeper patterns through mapping the co-occurrence of answers on any multiple-choice, multiple-answer survey question. Example Questions for AWARD's monitoring and evaluation: • Which combinations or "clusters" of crop/animal specializations are most common among applicants? • Which applicants bridge the common specialization clusters and do their characteristics differ from those of other cluster members on average? • Do applicants specializing in cattle tend to report also specializing in a greater diversity of plant species as compared to those specializing in goats or poultry?
Short-Loop Feedback	Utilization: provide quick feedback on potentially useful connections and overlaps. Example Questions: • What knowledge, skills, or resources could project stakeholders be exchanging for mutual benefit?
Bibliometric Analysis	Utilization: track influence and positioning of publications within fields. Example Questions for AWARD's monitoring and evaluation: • Do fellows tend to publish in the same fields and sub-fields? • How influential are fellows' publications? Do they appear to be more influential in some fields than in others?*****

Network questions on surveys	Utilization: examine a broad array of monitoring and evaluation questions regarding relationships between people, organizations, or other entities of interest. Although a single survey can suffice to produce rich datasets, asking the same questions over repeated surveys to generate panel data allows analyses to make stronger statements about change over time. The most common types of questions aimed at forming a picture of personal networks and social capital formation fall under the category of "name generators". For example: Modified Multiple Generator (MMG): Who are the (1-6) people with whom you discuss important matters? Positional Generator: By thinking of all the people with whom you are in contact, who is the [first/second/third] person who you would approach to gain access to influential researchers in your field? Example Questions for AWARD's monitoring and evaluation: • To what degree do fellows tend to follow similar career pathways, passing through the same or similar institutions? • Which institutions tend to be most influential in terms of attracting or producing the most empowered research professionals? How do these institutions relate to one another in terms of communication? Over time, how much do they tend to exchange professionals amongst each other?

***** *Common indicators of publication impact, including Journal Impact Factors, are developed through bibliometric methods based on SNA.*

The first and most important step in the application of SNA is to make an explicit plan that clearly shows which evaluation questions will be answered using SNA, and how the results of SNA will be integrated with those generated through alternative methods.

- How do relationships fit into program theory?
- To what extent can you be confident that collecting high-quality SNA data will be feasible (Table 2)?
- What will be the unit of analysis? What will the connections represent?
- What type(s) of result(s) will inform your decision (e.g. visualization, distribution of measures of centrality, regression analysis using measures of centrality, sub-group identification)?

It is important to pay close attention to special methodological concerns when framing questions and the survey distribution plan. Table 2 displays some frequent issues of concern that can decrease the quality of data.

Application of SNA in practice - AWARD's Retrospective SNA Project

This section addresses how applying SNA within AWARD's monitoring and evaluation framework demonstrates the value of SNA from a program design perspective. AWARD implemented a Retrospective SNA Project between February and May of 2016 with two overarching objectives:

Table 2: Primary concerns for collection of network data

Concern	Explanation	Potential Solutions
Missing Data	SNA is more sensitive to missing data than other statistical methods. To gain a cursory understanding of why, imagine removing a piece of data in a traditional statistical analysis – only the information from that data point is lost. Now, imagine removing a node from a network – both the node and all of its relationships with other nodes are lost.	Carefully design reasonable sampling methods. If you are not sure you can get data for all of nodes in a network, know that missing data may severely bias results.
		Invest heavily in thorough, high-quality data collection. For example, reserve time to follow up with fellows who do not completely answer survey questions relevant to network analyses.
Informant Bias	Consists of: (a) false recall of connections that never existed/happened, (b) forgetting, underreporting connections.	Check data for consensus between respondents. High degrees of consensus are strongly correlated with valid answers.
	Can be systematic: Respondents tend to falsely recall central alters and forget peripheral alters; respondents tend to forget infrequent interactions and falsely recall frequent interactions (which never actually happened).	Find ways to triangulate informant data with other sources. For example, for a subsample of respondents reporting on frequency of email contact, gain permission to digitally track actual email contact.
Reliability	Respondents may offer different answers to the same question if tested repeatedly.	Test-Retest: Repeat the same question over time and measure consistency. Factor inconsistency into measures of uncertainty.

First, the project sought to investigate the hypothesis that the relationships established within the fellowship can drive the formation of social capital, a key resource for advancing professional careers (Owen-Smith and Powell, 2004)[4]. This hypothesis underpins two central elements of AWARD's Theory of Change:

- An expansion of "agency", defined as "what a person is free to do and achieve in pursuit of whatever goals or values he or she regards as important" (Sen, 1985, p. 130). The program's theory of change correlates with empowerment as expansion of agency (Alkire and Ibrahim, 2007).
- The institutional environment and its "opportunity structure", which offers people opportunities to exert agency fruitfully. AWARD fellows are supported in becoming members of professional associations, attending scientific conferences, and completing research attachments. The premise is that ideas, resources, etc. pass from one individual,

group, or system unit along lines of geographic proximity and social interaction (Owen-Smith and Powell, 2004; Ahuja, 2000; Moody and White, 2003; Chandrasekhar, Kinnan and Larreguy, 2011; Jackson, Rodriguez-Barraquer and Tan, 2012). Relationships formed through these activities should therefore yield increased social capital and professional advancement opportunities.

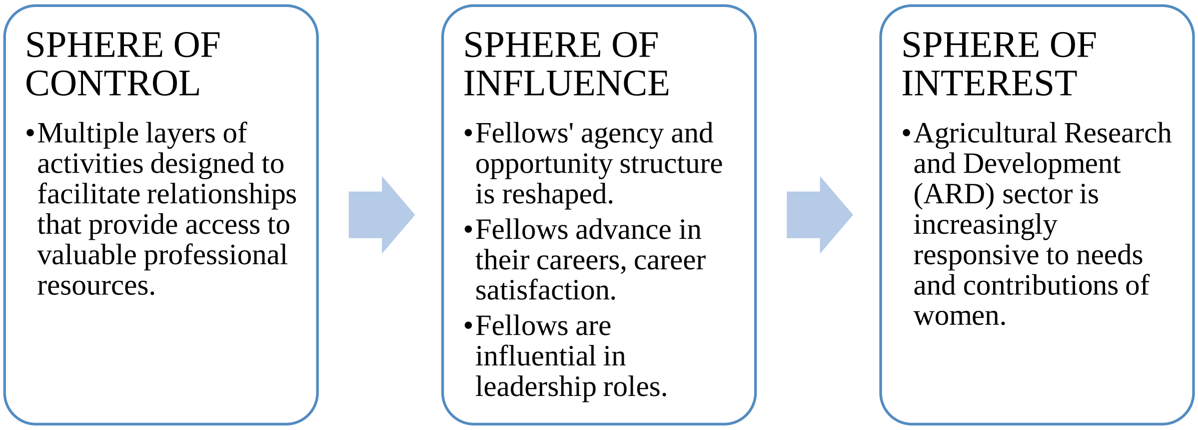

Figure 4: Summary of AWARD Theory of change focused on networks

The aspiration is that within the program’s broader sphere of influence, fellows’ enriched opportunity structures, social capital, and technical skills will put them in positions to contribute to agricultural research and also development, and play leadership roles in the sector.

The second overarching objective, perhaps equally as important as the first, was to provide the AWARD evaluation team with experience of doing SNA from start to finish, building capacity and paving the way for the more permanent inclusion of SNA in the program’s suite of evaluation methods.

The Retrospective SNA Project sought to answer the following questions:

- What measures or indicators can be used to best understand whether networking is in fact taking place?
- Which elements of the program’s strategies and theory of change intentionally (and unintentionally) facilitate networking?
- What factors within and outside of the fellowship (for example geographical proximity or institutional membership) facilitate networking?
- In what ways, if any, is networking associated with the program’s identified empowerment outcomes?
- How should AWARD better measure network mechanisms and benefits in the future?

The steps of the analysis are outlined below.

Data collection

Taking advantage of existing data
Under certain circumstances, SNA can be applied to pre-collected data from other monitoring and evaluation methods. The Retrospective SNA project analyzed data from four cohorts of fellows during the period 2008 to 2011, collected through the four survey instruments detailed in Table 3.

Table 3: Survey instruments used in the Retrospective SNA Project

Survey Name	Survey Sample	Survey Administration Moment
Application Form	All AWARD applicants	Rolling basis, as applications are submitted
Post-Fellowship Feedback Form	All AWARD fellows	At the end of the fellowship
Final Evaluation Survey Form	All AWARD fellows	At the end of the fellowship
Impact Story Form	All AWARD fellows	At the end of the fellowship

To provide useful, actionable results, the project focused only on known, current areas of interest for leadership. Four areas of interest were specified (Table 4).

Table 4: Themes for analysis, AWARD Retrospective Network Analysis Exercise

Theme	AWARD's Interest	Relevant Pre-Collected Data
Professional Associations	Similar to conferences, AWARD funds fellows' membership in professional associations. AWARD leadership has pending questions regarding the worth of this support as opposed to other, cheaper options such as distance learning and webinars.	The network exercise dataset contains 47 variables directly related to professional associations, including four that are the names of the individual associations themselves. These four name variables can serve to form both within-fellow and between-fellow networks graphs.
Positions & Organizations	AWARD recruits both mentors and mentees from a network of institutions involved in African agricultural research. Each institution has unique interests, reputation, resources, and culture (including attitudes towards women's involvement in research) which may enhance or impede its involvement with AWARD's beneficiaries. AWARD leadership perceived an opportunity to increase the efficiency of time and effort spent interacting with each of these institutions.	AWARD tracked the positions and organizations fellows took on as they progressed through the fellowship. The name variables for these organizations and positions can be used to form between- and within-fellow edges. Although the vertices met the requirements outlined above, so few fellows reported moving through institutions (within-fellow) or being part of the same institutions as other fellows (between-fellow) that the networks produced did not yield interesting analyses. The datasets produced by these models are included in the project deliverables.

 DOI: 10.19268/JGAFS.212017.7

Conferences	AWARD provides financial support for fellows to attend scientific conferences. Over 60% of fellows who took advantage of this support went to international conferences. AWARD desires to understand better the benefits of conference attendance for fellows, particularly those related to social capital construction, with the hypothesis that this support could be provided more efficiently.	The dataset for this retrospective SNA exercise does not contain variables that specify conference names or associated institutions, and therefore no appropriate candidate Vertex Variables.
Mentoring	AWARD wishes to better understand which mentor types and mentorship strategies have most influenced fellows' experiences.	While the dataset contains 21 variables related to mentors, only three of these – Mentor ID, Mentor Last Name, and Mentor First Name – are well suited to form network edges. Because each fellow only had one mentor, edges would provide the richest basis for SNA. Mentor ID must be excluded due to missing cases (75 of 249). Aggregating fellows by Mentor Last Name and Mentor First Name shows that AWARD selected 215 unique mentors. Only 20 mentors are associated with more than one fellow, which severely reduces the utility of a between-fellow comparison.

The project team identified variables relevant to these areas within the dataset and profiled them against two fundamental criteria for rich, interesting SNA.

Table 5: Example model setup – professional associations

Network Component	**Definition**	**Attached Metadata**
Vertices	Professional Associations in which fellows were members (within-fellow edge).	Measures of centrality: degree, closeness, eigenvector, betweenness. Average rating of significance of professional association membership to career growth by all fellows who were members. Percentage of fellows who were members of a professional association pre-AWARD fellowship.

 DOI: 10.19268/JGAFS.212017.7

Edges	Two Professional Associations share an edge when a fellow reports being a member of both simultaneously.	"Weight": Number of fellows who were members of both professional associations.

Data analysis

As is common in quantitative methods, the bulk of time spent on SNA is often dedicated to reformatting or reshaping data. In this project, raw data were imported into [R] statistical software[6] and then cleaned (e.g. standardizing the spelling of professional association names). The [R] script then reshaped the cleaned dataset into the Vertex List and Edge List. This transformation involved data organization (re-arrangement without adding or subtracting information) and data manipulation (variable aggregation using sums/count/average). Metadata were then calculated and merged in with the Vertex and Edge Lists to form the final dataset (Table 6).

Table 6: Vertex and edge list examples

Vertex List: *Data on entities is stored in a table similar to standard datasets with each unit of analysis on a different row, and the characteristics of each unit (variables) stored in the columns.*	**vtx.id**	**Degree Centrality**	**Betweenness Centrality**
	africa technology policy studies network	1	0
	african crop science society	4	4
	african nutrition society	5	37.60
	...	...	...
	world poultry science	3	0
Edge List: *Data on relationships is stored in a table where each row is a relationship and the first two columns, Vertex 1 and Vertex 2, define the related vertices. Subsequent columns can store metadata on the relationship.*	**vtx.1**	**vtx.2**	**weight**
	african nutrition epidermiology	african nutrition society	1
	african nutrition society	agricultural extension society of nigeria	1
	african association of agricultural economics	american association of agricultural economics	1
	...	...	...
	sustainable aquaculture research networks in sub-saharan africa	world aquaculture society	2

We used the [R] package graph to calculate network metrics such as measures of centrality7. The fully prepared network dataset was then exported from [R] to an Excel spreadsheet. NodeXL, a free Excel template for network visualization, was used to create visualizations for presentation8.

Interpreting and using SNA results

Using SNA results should always be a process of triangulation with other monitoring and evaluation methods. In this case, a combination of SNA and descriptive statistics presents an image consistent with the notion that AWARD broadens fellows' geographic horizons, shifting their participation from locally-based professional associations to regional and international associations where they previously had few connections. Specifically, fellows who end up on the outer edges of the professional association networks, i.e. those who share few overlaps with other fellows, also score highest in terms of their leadership capability[9].

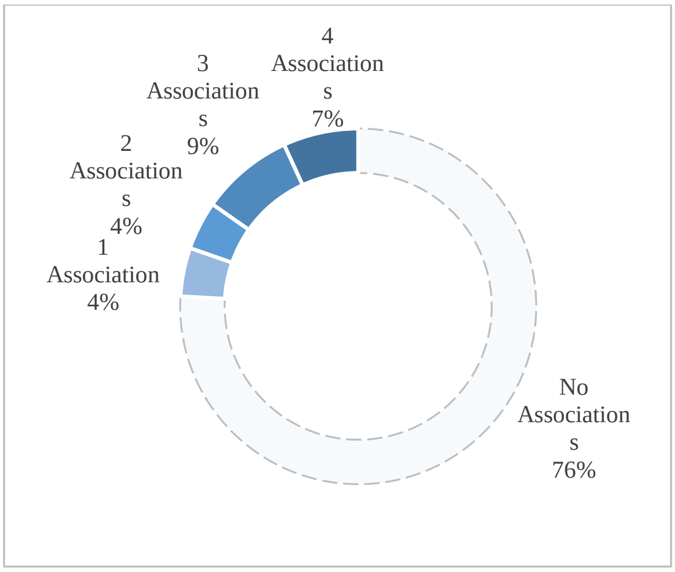

Figure 5: Distribution of membership by number of prof. associations

Of the 249 fellows represented in the project dataset, 60 (24 percent) reported belonging to at least one professional association, and 49 (20 percent) belonged to two or more.

Table 7: Distribution of professional association membership

	Distribution of Memberships*		Distribution of Associations		Year Started Membership	
Geographic Scope	#	Pct.	#	Pct.	Avg. Year Joined**	% before becoming fellows
Africa-wide	8	10%	5	10%	2011	53%
International	47	61%	29	54%	2011	14%
National	20	26%	18	33%	2005	88%
Sub-Regional	2	3%	2	4%	2012	1%
Column Sum	77		54			
Mean (all assoc.)					2009	40%

*It is important to note that this table counts memberships, not fellows. Each fellow may be a member of multiple associations.** Arithmetic mean rounded to closest year.

Membership in professional associations is not only relatively rare, but also spread sparsely among 54 different associations (Table 7).

Although verification of the direction of causality is impossible given the dataset, the results could support a story in which AWARD tends to encourage fellows to network across borders, and in particular, beyond Africa. Geographically, the distribution is skewed towards international associations (61 percent of all memberships distributed among 47 associations). Fellows also tended to join national associations earlier (on average, in 2005) than international associations (on average, in 2011).

Descriptive analyses show that there is no correlation between registering to a professional association and gains in levels of empowerment – specifically increasing fellows' capabilities and opportunities to achieve professional autonomy. Additionally, fellows were unlikely to list membership to professional associations as one of the activities that made a significant contribution to their empowerment. With SNA, however, we can gain a more nuanced view by integrating the influence of relationships between fellows and associations into analyses.

Within-fellow network model: professional associations connected by fellows

In the within-fellow model (Figure 10), each node represents a professional association. A connection (edge) appears when one or more fellows are members of both associations[10]. One could interpret this network as the web of professional associations "bridged" by fellows. The shape of the network shows how fellows have decided to distribute memberships when joining multiple professional associations.

An inspection of the network visualization reveals that fellows (a) do not usually belong to multiple professional associations, and (b) tend to be spread thinly throughout diverse associations. These results align with the fellowship's broad, multi-themed focus and intentional selection of fellows from disparate fields of agricultural research. Some sub-groups, like the four light blue squares in Figure 9 (all associated with agricultural economics), have clear thematic focuses, while others like the light blue circles on the bottom left seem to depend more on the popularity of a central organization (the Microbiology Society in this case).

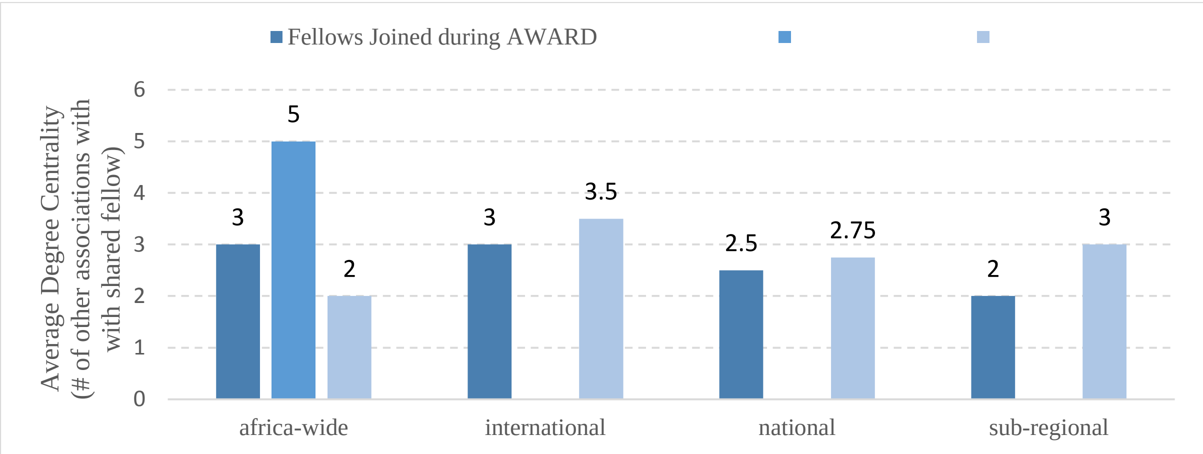

Figure 6: Avg. degree centrality by geographic scope and moment joined

Figure 6 shows that after joining the fellowship, fellows tend to become part of professional associations of which other fellows are not members. This could be another indication that AWARD is helping fellows broaden their horizons and branch out beyond the standard associations they and their peers would usually join. The graph compares associations where fellows joined before AWARD versus those joined during AWARD, based on the average number of fellows they

 DOI: 10.19268/JGAFS.212017.7

share with other associations (degree centrality). Associations which fellows joined pre-AWARD share more fellows with other associations than those which fellows joined post-AWARD (except in the Africa-wide group).

Between-fellow network model: network of fellows as connected through professional associations
In this second model, each node represents a fellow (a person) and edges show when two fellows are members of the same professional association. The 49 vertices represent the 20 percent of fellows who share a professional organization with at least one other fellow. Conceptually, this model represents the network of fellows connected through professional organizations who might, for example, see each other at conferences or correspond over association listservs.

Analysis reveals that fellows tend to cluster in cliques. Within each clique, every member is connected to every other member. With few exceptions, each clique corresponds to a group of fellows who all belong to a single association. Figure 7 indicates that Ethiopian fellows overlap most in terms of professional association membership, sharing an average of five or more connections with other fellows. Tanzanians rank second, while Nigerians – roughly a third of fellows represented in the network – come in third. This analysis provides an actionable result: to efficiently disperse fellows, i.e. aim them where their peers are not already members, the fellowship could prioritize these three nationalities.

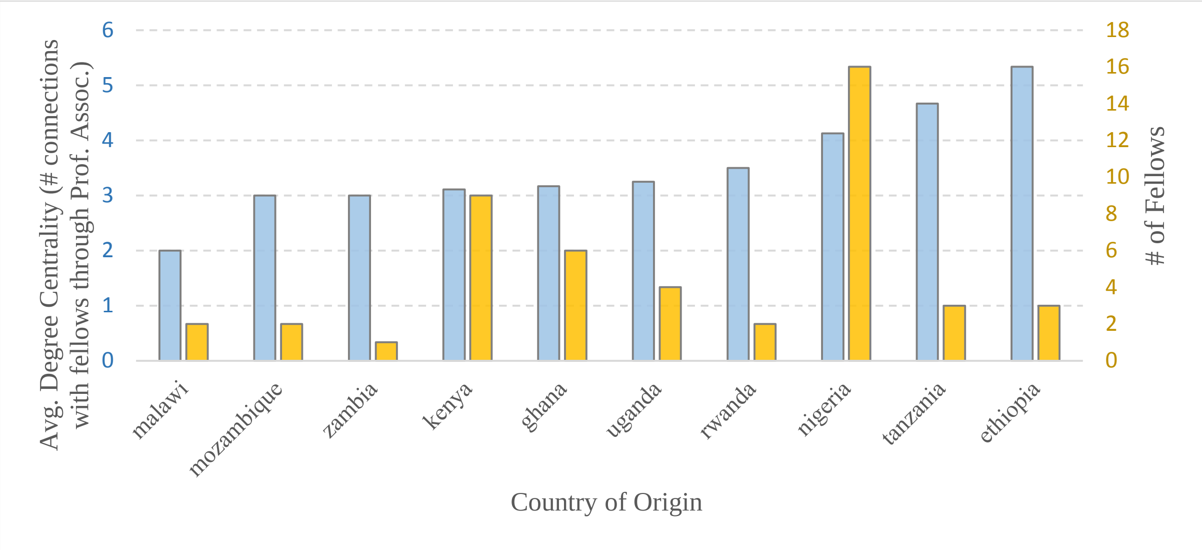

Figure 7: Prevalence of professional association overlap between fellows by country

Figure 8 demonstrates that fellows who score themselves high in leadership capabilities tend to be connected to fewer fellows through professional associations. These fellows are also more likely to belong to multiple associations. Both tendencies also align with the hypothesis that AWARD encourages fellows to expand their professional networks beyond familiar boundaries and in doing so boosts their self-rated leadership capacity. Alternatively, the fellows who tend to view themselves as more capable leaders could be those who are the most likely to branch beyond the networks they share with their peers (this analysis cannot tell the direction of the cause-effect relationship).

 Vol 2, Issue 1, 2017 pp 125-148

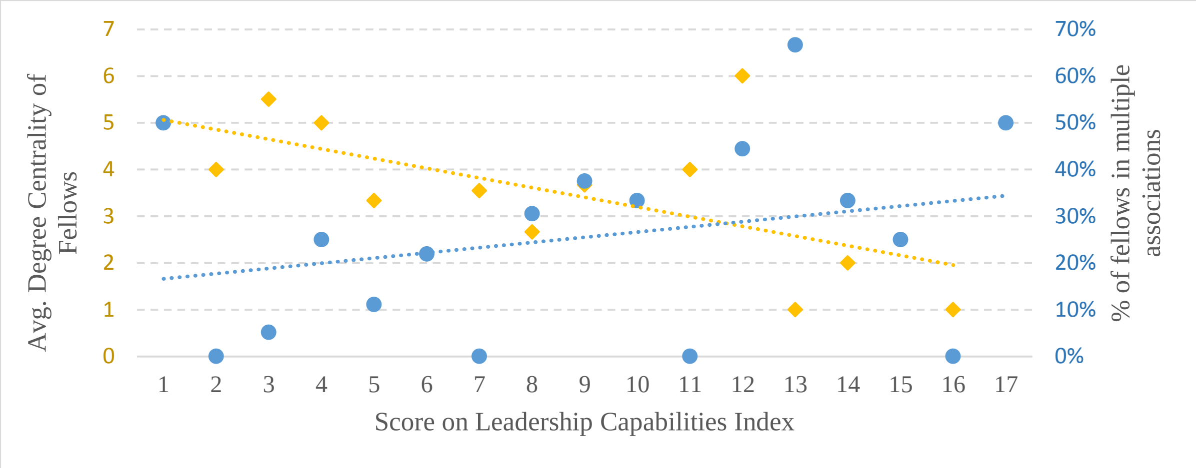

Figure 8: Leadership capabilities index vs. fellows' degree centrality

Looking at sub-groups within this model supports the claim that sharing connections with other fellows through professional associations is a sign of "greenness". Three groups in the upper-left portion of Figure 10 link to each other through a single "pass-through" fellow[11]. Observing the comparison between these pass-through fellows and other fellows displayed in

Table 8: Pass-through vs. non-pass-through fellows – summary stats

	non-pass-through	pass-through
# fellows	45	3
origin countries		
avg. degree	2.7	4.0
avg. betweenness	4.2	81.3
avg. closeness	0.00056	0.00073
avg. eigenvector	0.145	0.675
avg. leadership capability index	7.6	6.3
avg. power over index	5.2	3.0
avg. power within index	2.6	1.3
avg. power to empower index	1.5	1.3

 DOI: 10.19268/JGAFS.212017.7

Table 8, we see that pass-through fellows' leadership and empowerment indices are universally lower than those of their peers. Once again, the image presented by the data is that the more highly connected pass-through fellows in this network are less experienced; more seasoned, independent fellows exist on the edges[12].

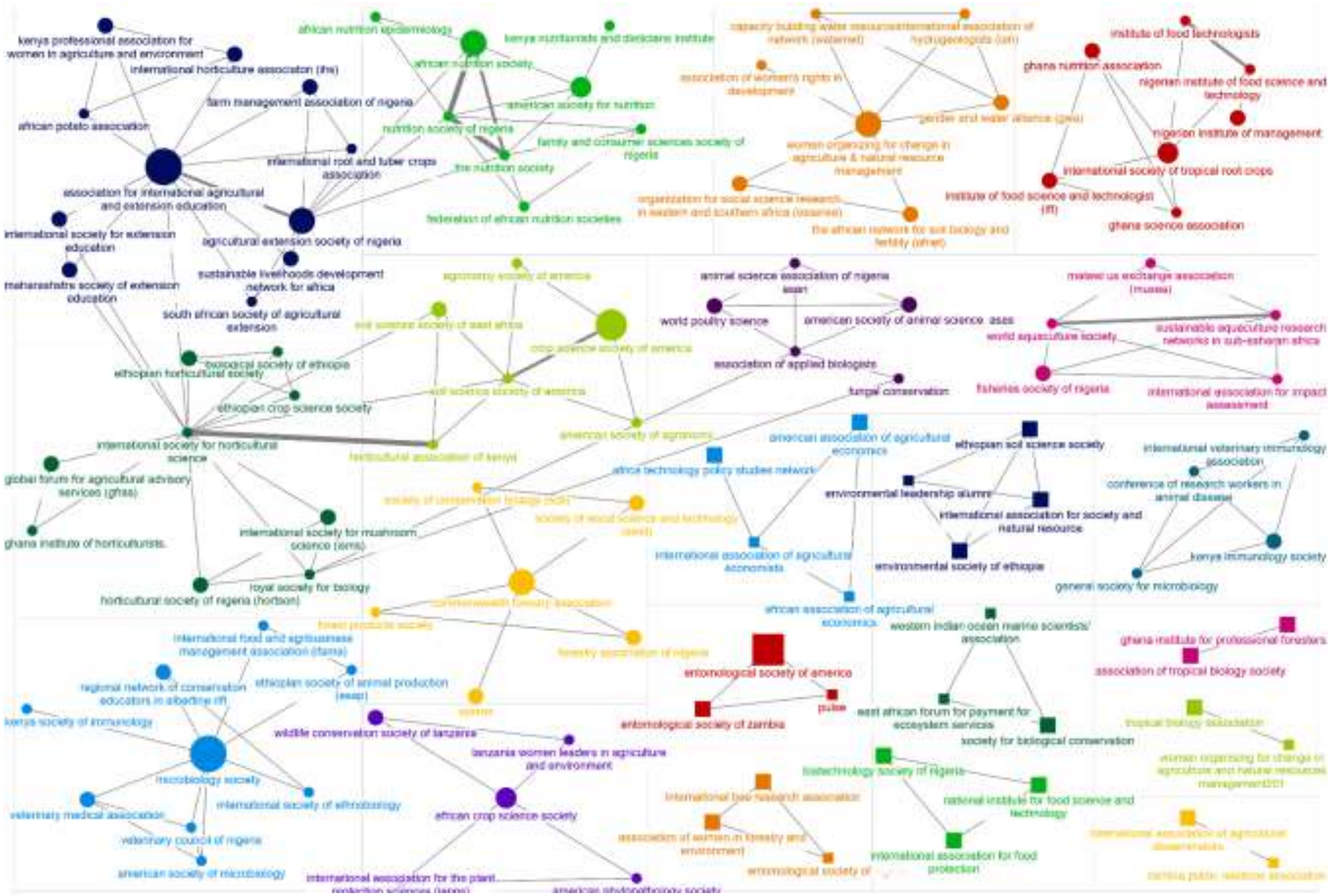

Figure 9 Legend

Graph Feature	*Definition*
Vertex Size	Depends on number of fellows who are members of the prof. association
Vertex Shape & Color	Different for each (sub-group as defined the Girvan-Newman clustering algorithm)
Edge Width	Depends on the number of fellows reporting membership in both prof. associations (max = 3)
Layout	According to Harel-Koren Fast Multiscale Method

Figure 9: Professional associations as connected by fellows

 DOI: 10.19268/JGAFS.212017.7

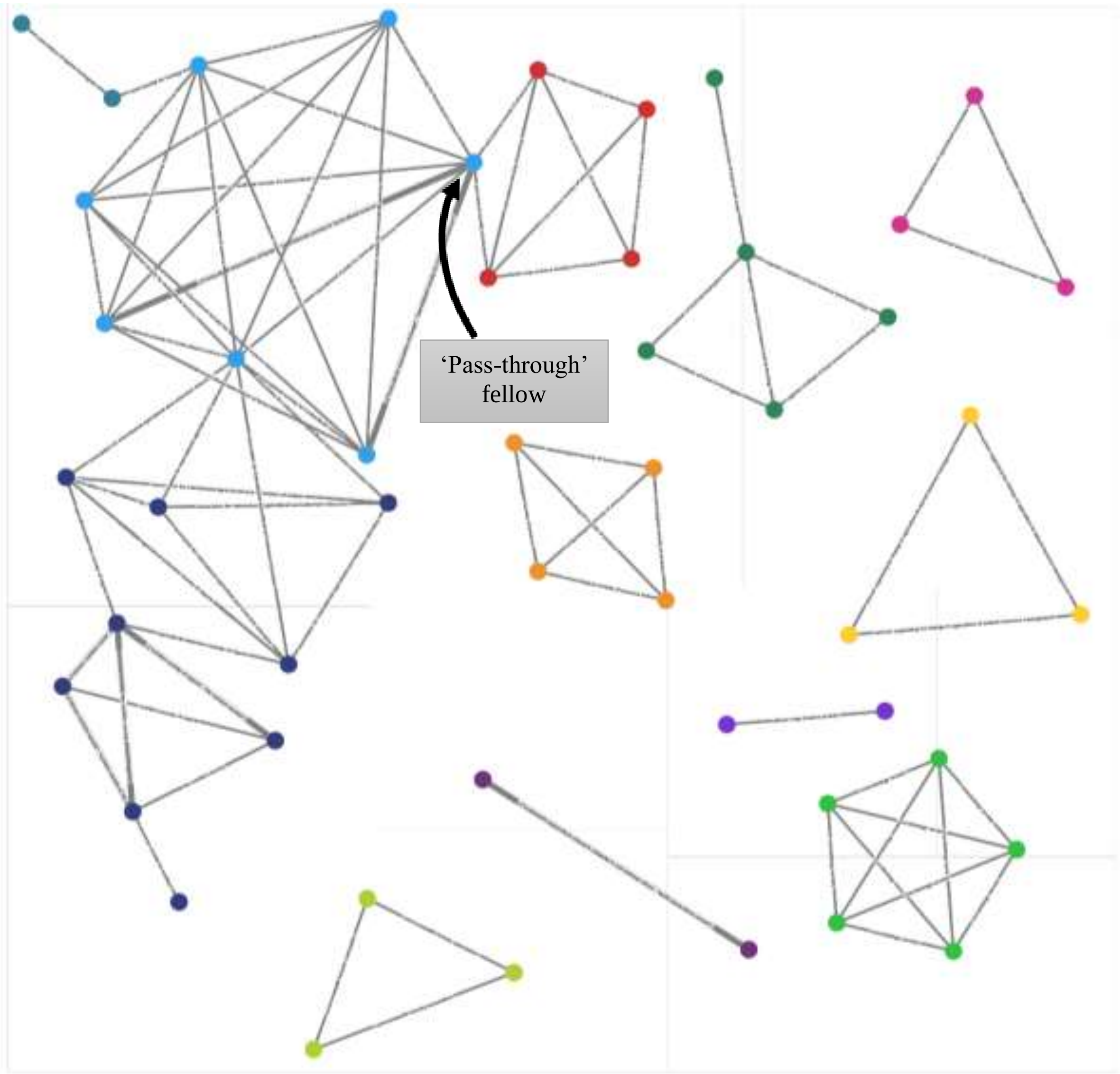

Figure 10 Legend

Graph Feature	*Definition*
Vertex Size	Constant
Vertex Color	Different for each sub-group as defined the Girvan-Newman clustering algorithm
Edge Width	Constant. Labels according to prof. association(s) in which both fellows report membership.

Figure 9: Network of fellows as connected through professional associations

Conclusion

This paper examines why and how rigorous SNA should be applied with greater frequency in the evaluation of agricultural research and development, and capacity-building development interventions. The relationships between units of analysis in these programs, whether individuals, organizations, countries, or otherwise, are both influential and too often ignored by other quantitative evaluation methodologies.

AWARD has astutely identified SNA as a method that can furnish evidence relevant to some of the program's primary objectives and activities. The Retrospective SNA Project demonstrates that for a limited set of themes, AWARD has already collected data amenable to SNA that can supplement ongoing monitoring and evaluation activities. The project exploited existing monitoring and evaluation data to: identify elements of AWARD's interventions, strategies and theories of change that intentionally (and unintentionally) facilitate networking; understand which factors within and outside of the fellowship (related to geographical proximity, social interactions, etc.) facilitate networking; examine how networking is associated with empowerment outcomes; and to discuss how AWARD should measure network mechanisms and benefits better in the future.

From this analysis we highlight that:

- There are many ways in which AWARD's theory of change is intentional about connecting scientists.
- After joining the fellowship, participants, fellows move from locally-based professional associations also joined by close peers, into regional and international associations where they previously had few connections. This evidence is consistent with the hypothesis that AWARD broadens geographic horizons.
- Fellows are dispersed throughout a broad network of professional associations (more than 50 associations between 2008 and 2011), as would be expected given their diverse origins and disciplines. However, Ethiopian, Tanzanian, and Nigerian fellows tend to join the same professional associations as their peers. AWARD will need to investigate further to understand the causes of these patterns.
- When fellows are part of professional associations of which other fellows are not members, this is associated with higher scores on empowerment indices. Fellows who end up on the outer edges of the professional association networks, i.e. those who share fewer overlaps with other fellows, score highest in terms of their leadership capabilities and empowerment indices. Although far from causal, this result deserves further investigation.

At the same time as it provided the above conclusions, the Retrospective SNA Project served as a proof-of-concept for a larger claim: evaluators and evaluation commissioners in international development should place relationships high on the list of explanatory factors and make their examination a priority. SNA is a broadly applicable family of analysis techniques which deserve greater attention and higher rates of application in the evaluation of capacity building interventions. In other words, when proposing evaluation methods, the onus should be on evaluators and commissioners to explain why SNA is *not* applicable, rather than vice versa.

Endnotes

[1] Technically speaking, hierarchies are a type of network and can also be studied using SNA. The distinction of note is that an evaluation of the efficiency of a strictly hierarchical intervention with a known structure would traditionally measure indicators such as what percentage of resources reached the target population. The analysis might subset these pieces of the hierarchy, such as country or department. In a non-hierarchical network, however, such as a nonprofit coalition, with resources flowing from multiple sources to multiple endpoints and a shifting, distributed leadership structure, measuring these traditional indicators and divisions is difficult. As we shall show throughout the paper, SNA empowers evaluators with tools to assist in understanding these messier by opening the possibility of integrating quantitative analysis of network structure, strength,

density, etc.

[2] Rather than specify that the entities in question must be human, the term "social network analysis" helps to distinguish this application of the network theory to social phenomena as opposed to electrical circuits or computer networks (two other common applications of the same mathematical tools).

[3] In SNA, relationships (as well as entities) can also carry attributes. For example, in some networks, there is meaning to the "direction" of an edge. If an AWARD fellow moves from a post at Organization 1 to a post at Organization 2, the relationship between the two is "directed", with an arrow pointing from Organization 1 to Organization 2. Relationships can also carry measures of strength or intensity, such as the frequency of communication, as well as categorical qualities, such as whether that communication is in-person, via phone, email, etc.

[4]Project implemented February-May, 2016, in cooperation with Flux Research, Monitoring and Evaluation. Project final report available upon request. Please contact Apollo Nkwake (nkwake@gmail.com).

[5] The numbers 15 and 30 are informal rules of thumb, backed only in the empirical experience of the authors rather than SNA theory itself.

[6] Using [R] for these purposes requires significant investments in learning the [R] coding language. The same transformations could be accomplished in Excel or other spreadsheets software without the need for this investment, but would necessitate more time and incur greater risk of error (untraceable mistakes that alter raw data). [R] script available from authors upon request. Please contact william@fluxrme.com.

[7] Again, using the igraph package in [R] requires previous knowledge of the [R] language. A host of alternative software packages are available which can accomplish the same analyses. For a comprehensive list of these packages:
https://en.wikipedia.org/wiki/Social_network_analysis_software
The authors recommend UCINET as a common program with larger user base and extensive documentation for those entering the field.

[8] NodeXL is a project of the Social Media Research Foundation and may be downloaded from http://www.smrfoundation.org/nodexl/.

[9] We are careful with our language here. The methods applied here do not attempt to measure outcomes over time, nor do they include any comparison groups. We do not know the direction of causality. The data equally support two cases: (a) that AWARD increasing leadership capacity and that these empowered fellows join different professional associations than their peers, or (b) that those AWARD fellows who have the highest leadership capacity to begin with are those that tend to position themselves on the outer edges of the network of professional associations.

[10] A more legible high-resolution version of this image is available upon request. Please contact william@fluxrme.com.

[11] "Pass-through" fellows are defined as those nodes in the network with connections to more than one sub-group.

[12] Further research on the network structure might permit deeper examination of the value of these bridging relationships and contribute to the literature on their value to social capital formation in diverse cultural contexts (Burt, Hogart and Michaud, 2000).

References

Ahuja, G. (2000) ‘Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study’, *Administration Science Quarterly,* 45(1), pp. 425-455.

Aigner, S. M., Flora, C. B. and Hernandez, J. M. (2001) ‘The Premise and Promise of Citizenship and Civil Society for Renewing Democracies and Empowering Sustainable Communities’, *Sociological Inquiry,* 71(Spring), pp. 493-507.

Alkire, S. and Ibrahim, S. (2007) ‘Agency & empowerment: a proposal for internationally comparable indicators’, *Oxford Development Studies,* 35(4), pp. 379-403. Available at: http://www.tandfonline.com/doi/abs/10.1080/13600810701701897

Burt, R. S. (2000) ‘The network structure of social capital, *Research in Organizational Behavior,* 22, pp. 345-423. Available at: http://doi.org/10.1016/S0191-3085(00)22009-1

Burt, R. S., Hogarth, R. M. and Michaud, C. (2000) ‘The social capital of French and American managers’, *Organization Science,* 11(2), pp. 123-147. Available at: http://doi.org/10.1287/orsc.11.2.123.12506

Chandrasekhar, A. G., Kinnan, C. and Larreguy, H. (2011) ‘Informal insurance, social networks, and savings access: evidence from a lab experiment in the field’. MIT Working Paper. Available at: http://ibread.org/bread/sites/default/files/1012conf/Chandrasekhar.pdf

Dershem, L. and Bokuchava, T. (2016) ‘Network weaving for regional development: an evaluation of the Caucasus' agricultural alliances in Armenia and Georgia using social network analysis’. Oxfam Research Report. Available at: http://www.betterevaluation.org/sites/default/files/Network%20Weaving%20for%20Regional%20Development.pdf

Emery, M. and Flora, C. (2006) ‘Spiraling-up: Mapping Community Transformation with Community Capitals Framework’, *Community Development,* 37(1), pp. 19-35.

Falk, I. and Kilpatrick, S. (1999) ‘What is social capital? A study of interaction in a rural community’, *Sociologia Ruralis*, 40(1), pp. 87-110. Available at: http://onlinelibrary.wiley.com/doi/10.1111/1467-9523.00133/abstract

Fowler, J. H. and Christakis, N. A. (2008) ‘Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study’, *British Medical Journal,* 2008(337), a2338. Available at: https://doi.org/10.1136/bmj.a2338

Fruchterman, T. M. J. and Reingold, E. M. (1991) ‘Graph drawing by force-directed placement’, *Software: Practice and Experience*, 21(11), pp. 1129-1164. Available at: http://doi.org/10.1002/spe.4380211102

Girvan, M. and Newman, M. E. J. (2002) ‘Community structure in social and biological networks’. *Proceedings of the National Academy of Sciences of the United States of America*, 99(12), pp. 7821-7826. Available at: http://doi.org/10.1073/pnas.122653799

Hoppe, B. and Reinelt, C. (2010) ‘Social network analysis and the evaluation of leadership networks’, *The Leadership Quarterly,* 21(4), pp. 600-619. Available at: http://doi.org/10.1016/j.leaqua.2010.06.004

Hu, Y. (2011) ‘Algorithms for visualizing large networks’, in Naumann, U. and Schenk, O. (eds.) *Combinatorial Scientific Computing*. Florida: CRC Press, pp. 1-25.

Jackson, M. O., Rodriguez-Barraquer, T. and Tan, X. (2012) ‘Social capital and social quilts: network patterns of favor exchange’, *The American Economic Review,* 102(5), pp. 1857-97.

Available at: http://doi.org/10.1257/aer.102.5.1857

Knoke, D. and Yang, S. (2008) *Social Network Analysis.* Second edition. Thousand Oaks, CA: Sage Publications.

Koren, Y., Carmel, L. and Harel, D. (2002) 'ACE: a fast multiscale eigenvectors computation for drawing huge graphs', *IEEE Symposium on Information Visualization, INFOVIS* 2002. *Proceedings.* 28 - 29 October. IEEE, pp. 137-144. Available at: https://pdfs.semanticscholar.org/716f/503252971f05a1305349f688c1812fc7cc65.pdf

Krackhardt, D. (1994) 'Graph theoretical dimensions of informal organizations', in Carley, K. M. and Prietula, M. J. (eds.) *Computational Organization Theory.* New Jersey: Lawrence Erlbaum Associates, pp. 89-111.

Lin, N. (1999) 'Building a network theory of social capital', *Connections*, 22(1), pp. 28-51. Available at: http://www.insna.org/PDF/Keynote/1999.pdf

Martınez, A., Dimitriadis, Y., Rubia, B., Garrachon, G. and Marcos, J. (2003) 'Combining qualitative evaluation and social network analysis for the study of classroom social interactions', *Computers & Education*, 41(4), pp. 353-368. Available at: http://www.sciencedirect.com/science/article/pii/S0360131503000824

Moody, J. and White, D. R. (2003) 'Group Cohesion, Nesting, and Embeddedness', *American Sociological Review*, 68(1), pp. 103-127.

Network Impact. (2014) *The state of network evaluation – a guide*. Available at: http://www.networkimpact.org/the-state-of-network-evaluation-a-guide/

Owen-Smith, J. and Powell, W. W. (2004) 'Knowledge networks as channels and conduits: the effects of spillovers in the Boston biotechnology community', *Organization Science*, 15(1), pp. 5-21. Available at: http://doi.org/10.1287/orsc.1030.0054

Reynolds, M. (2007) 'Evaluation based on critical systems heuristics', in Williams, B. and Imam, I. (eds.) *Systems Concepts in Evaluation: An Expert Anthology*. Point Reyes, CA: EdgePress, pp. 101-122.

Seibert, S. E., Kraimer, M. L. and Liden, R. C. (2001) 'A social capital theory of career success', *Academy of Management Journal*, 44(2), pp. 219-237. Available at: http://doi.org/10.2307/3069452

Sen, A. (1985) *Commodities and Capabilities*. Amsterdam: North-Holland.

Spielman, D. J., Davis, K., Negash, M. and Ayele, G. (2011) 'Rural innovation systems and networks: findings from a study of Ethiopian smallholders', *Agriculture and Human Values*, 28(2), pp. 195-212. Available at: http://doi.org/10.1007/s10460-010-9273-y

Valente, T. W., Gallaher, P. and Mouttapa, M. (2004) 'Using social networks to understand and prevent substance use: a transdisciplinary perspective', *Substance Use & Misuse*, 39(10), pp. 1685-1712. Available at: http://doi.org/10.1081/LSUM-200033210

Wasserman, S. and Faust, K. (1994) *Social Network Analysis: Methods and Applications.* Cambridge: Cambridge University Press.

Wood, B. A., Blair, H. T., Gray, D. I., Kemp, P. D., Kenyon, P. R., Morris, S. T. and Sewell, A. M. (2014) 'Agricultural science in the wild: a social network analysis of farmer knowledge exchange', *PLoS ONE*, 9(8), e105203. Available at: http://doi.org/10.1371/journal.pone.0105203