PHILIPP AGRIC SCIENTIST
Vol. 103 Special Issue, 40-52
December 2020

ISSN 0031-7454

Analyzing Social Networks in Upland Farming Communities for Improving Design of Education and Information Programs: The Case of Atok, Benguet

Aubrey D. Tabuga[1,*], Anna Jennifer L. Umlas[1], and Katrina Mae C. Zuluaga[1]

[1]Philippine Institute for Development Studies

[*]Author for correspondence; e-mail: ATabuga@mail.pids.gov.ph

This study examines the structure of social networks in three upland farm communities in Benguet Province to develop insights about how information and education campaigns can be designed to more effectively reach farmers located in remote and geographically constrained areas. In the Philippines, there is a significant human resource gap in extension workers. It is therefore important to explore mechanisms that can help address this gap. The idea is to use the prevailing social norms in communities to identify, through social network analysis, central actors who can potentially aid in extension work as well as peripheral actors who may be reached through a different approach. We found that upland communities have varied social network densities and that network centrality of actors is associated with having the means to move around and one's physical proximity to venues for social gathering. We conclude that information and education campaign (IEC) approaches can be improved by accounting for differences and nuances in the social structures in their design and implementation. Targeting central actors in the communities in IECs and providing an incentive mechanism for these to aid in extension work through echoing and social influencing are potentially effective strategies that can be implemented in contexts of inadequate human and financial resources. At the same time, a more direct approach for reaching and benefiting actors who are not well-integrated into the social systems will ensure that these are not left behind.

Keywords: social network analysis, agricultural extension

Abbreviations: IEC—information and education campaign, ATI—Agricultural Training Institute, LGU—Local Government Unit, CBMS—Community Based Monitoring System

INTRODUCTION

Agricultural extension workers are often searching for more effective strategies for reaching and disseminating information to farmers. Extension, defined as an "informal educational process directed toward the rural population" is the "means by which new knowledge and ideas are introduced into rural areas in order to bring about change and improve the lives of farmers and their families" (Khalid and Sherzad 2019). In the Philippines, the Agricultural Training Institute (ATI) is mandated to equip agricultural extension workers, craft learning programs for both farmers and extension workers, and communicate research and technology to farmers, fisherfolk and extension workers. Extension workers' tasks, therefore, include facilitating training, farm demonstrations, site visits, farm and business advisories, and the dissemination of information to stakeholders. Under the Local Government Code of 1991, the mandate of agricultural extension is under local government units (LGUs). Many LGUs, however, rely heavily on the Internal Revenue Allotment that comes from the national government for funding their programs, including agricultural extension (Declaro-Ruedas 2019). Often, there is a lack of agricultural extension workers to cover all areas, and there are limited studies on extension workers' actual extent of reach among farmers and farming households.

The problem of human resources is magnified in upland farming communities especially in remote, geographically constrained areas like the province of Benguet in the Cordilleras where the communication infrastructure is unimproved and mobility is significantly challenged by the rough terrain and long distances between communities. In Benguet Province, recent data show that only 134 agricultural extension workers were serving a total of 84,087 farmers. The study area, the municipality of Atok, has only seven extension workers serving its smallholder farmers. The relatively low extension worker to farmer ratio, the physical and infrastructural barriers, and other identified cognitive gaps between the availability of information and its use (Domingo et al. 2020) point to the need to explore strategies that are effective in reaching out to farmers in the area.

People in such extremely constrained areas may tend to rely more heavily on their networks for information and guidance. To what extent this is true in this region and how such information sharing is structured have not been examined in the past. Understanding the structure in such social systems may be useful in the design of more effective information and education programs and other interventions. The idea is to use the prevailing social norms to develop strategies that may require fewer resources on the part of the local government and other stakeholders, but still reach as many communities as possible.

This study uses social network analysis to develop insights for improving extension work in this upland area. Analyses of farmers' networks have been implemented in several countries,[1] but not yet in the Philippines' context. We examined the current state of the literature that examined farmers' networks. Many recent studies about farmers' networks examined the importance of networks within the context of information acquisition, sharing, or use (Pratiwi and Suzuki 2017; Vishnu et al. 2019; Maguire-Rajpaul et al. 2020; Beaman and Dillon 2018). They found that certain characteristics of farmers' networks are useful. In Vishnu et al. (2019), the homogeneity of farmers' networks is argued to facilitate information sharing and meaningful interactions. More extensive networks and a more central position within the network are associated with higher end-of-training test scores (Pratiwi and Suzuki 2017). This, the authors noted, implies that the knowledge-seeking behavior of farmers is correlated to their networking ability, though this finding seems to depend on the type of crop grown. Beaman and Dillon (2018) found that information diffusion declines with social distance or, in other words, information diffusion is more likely with social proximity. However, there may be distribution repercussions of targeting only central actors in a network (Beaman and Dillon 2018). Beaman and Dillon (2018) found that targeting nodes based on betweenness scores led to the exclusion of less-connected nodes from obtaining new information. The same study also noted that there were gender differences in the relationship between information diffusion and social distance. It was found that men were more likely to receive information and farming outputs than women were. Women in the study had 63% fewer contacts and were less central in the village. In villages where information was first targeted to more central nodes to disseminate, women also had significantly lower knowledge than when the information was given to random nodes. Also, in Cadger et al. (2016), it was found that women farmers have smaller networks than male farmers. Female farmers also had fewer network connections with individuals from other communities. Hoang et al. (2006) also corroborate that while targeting central nodes to disseminate information is sufficient to reach a broad circle, it may not be enough to reach nodes on the periphery, like women.

Personal contacts seem to be important in network formation. Wood et al. (2014) found that farmers with densely tied and similar occupations grew networks more than farmers whose networks were loosely tied and different. Farmers value knowledge delivered in person, primarily from fellow farmers, and seek information from farmers they know have similar farms and experiences (social homophily). This is similar to the finding of Vishnu et al. (2019), who also highlight that communication about new agricultural knowledge more likely happens in daily interactions rather than in organized meetings. As such, it is important to include the participation of central actors in the generation of knowledge. Ramirez (2013) found kin and fellow farmers as main sources of adaptation information in a farmer's social network, citing trust as a significant reason that farmers would rely more on each other than outside information sources. Similarly, Nidumolu et al. (2018) found that information sharing mechanisms in India include farmer relationships and both formal and informal institutions. Institutional information sources with a high degree of centrality were found to be village knowledge centers, cooperative representatives, and government and private extension workers, while weaker ties were to shop owners and government officials.

Influence within a social network, on the other hand, seems tied to individual characteristics such as educational achievement and access to other essential resources. Studies of a village in Northern Vietnam differentiate between discussion, advice, and action networks in the community, and find that while

[1] See Isaac et al. (2007) for Ghana, Pratiwi and Suzuki (2017) for Indonesia, Nidumolu et al. (2018) for India, Spielman et al. (2010) for Ethiopia, Wood et al. (2014) for New Zealand, Beaman and Dillon (2018) for Mali, Hoang et al. (2006) for Vietnam, among others.

discussion networks are fairly random, villagers approach village heads, identified opinion leaders and better-educated individuals for advice. Greater influence in the community is linked to positions in local government, which in turn are linked to larger kin networks, greater education, greater access, and more frequent visits from extension workers. Interviews with villagers revealed, however, that while these individuals were very central in the network, they were not necessarily good farmers and would also not necessarily be the best at extension work and disseminating information widely. Thus, in stark contrast to the advice networks, action networks (networks of those whose advice they follow) revolved primarily around kin, who villagers see have their best interests in mind (Hoang et al. 2006).

Other studies show that beyond pure social ties, an individual's actions (like choosing which crop to grow) can also impact adoption decisions. In Villanueva et al. (2016), larger farmer networks are associated with growing more crops, having more land, and subsequently a higher yield and economic value for crops sold. Farmers with larger networks had also diversified into improved crops and crop varieties. Cadger et al. (2016) also found that the size of knowledge networks also varied with the different crops that farmers produced. Wossen et al. (2013) also report that distance from an adopter of technology will also determine an individual's adoption behavior. Having larger networks with more relatives, friends, and neighbors, as well as the distance between network members and physical location of plots near adopters' farms, increases the chances of adoption of new farming and resource management practices. Proximate social distance from the giver also impacts the distribution of rival goods such as farming inputs, though the effect was not as pronounced with non-rival goods such as information (Beaman and Dillon 2018). Overall, a network's size and a farmer's position in it would depend on participation in development and training, crops cultivated, and individual characteristics such as gender and educational achievement. Social ties, physical proximity and the involvement of government and institutional actors also shape the interactions of agricultural stakeholders in the community and form important communication mechanisms between nodes.

The connections or links, and consequently the resulting network centrality scores, were defined in most studies based on who farmers share information or advice with (Hoang et al. 2006), and who they share their knowledge with (Wood et al. 2014).[2] While these approaches are useful for understanding access and the use of information and advice being sought out by farmers, they may not suffice for understanding the extent of social connectivity of the target population for purposes of using the network for more long-term information dissemination programs or social influencing schemes. This is because the extent of information sharing as well as those who people would seek advice from or give advice to are likely to change based on the nature of information and circumstance. It may be useful to gather more robust social links such as kinship, friendship, economic connections, and resource sharing relations. Unlike most studies, Beaman and Dillon (2018) combined relations on financial transactions, family relations, residential neighbors, farm plot neighbors, and organizations they were affiliated with to create the networks in their study using data from Mali. Beaman and Dillon (2018) also analyzed farmers' networks with nodes being defined at the household level rather than the individual level. This current paper uses a similar approach – analyzing networks in various ways and at the household level, but in the context of upland farm communities with significant constraints on mobility and communication, where the role of social networks may be magnified.

Although the general idea is to examine networks to improve information dissemination strategies regardless of the content or property that is being disseminated, this study augments the analysis by accounting for the current extent of the reach of extension workers in the upland communities through social network analysis to gain a better view of how recent efforts can be further improved. This paper is comparable in terms of objective, methodology and context with the study of Hoang et al. (2002) using the case of an upland village in northern Vietnam. Hoang et al. (2002) examined kinship and friendship links, communication networks, and mutual aid groups and their implications for agricultural extension. For its contribution, the current study uses the case of three different upland communities in the Philippines to enable comparison and, consequently, more nuanced analysis. It also examines not only kinship and friendship, but also peer advice and resource-sharing networks, and information networks much like Beaman and Dillon (2018). Another contribution is the use of econometric analysis to identify the characteristics of central actors.

Many previous analyses of institutional networks in Benguet are primarily descriptive, and detail specific institutions such as microfinance providers, farmers cooperatives and organic farmers' organizations over the

[2] See also Pratiwi and Suzuki (2017), Vishnu et al (2019), Maguire-Rajpaul et al. (2020).

wider spread of possible associations in the community. Likewise, descriptive local literature often frames social capital and networks within important familial and indigenous group ties. Much of this important research was also conducted earlier in the century, but acknowledges realities such as the uneven distribution of power in credit relationships heavily favoring the creditor, and likewise that favoring family in credit relationships may lead to increased transaction costs for both parties (Russell 1987) (Milagrosa and Slangen 2006), though a 2017 study by Reyes and other authors also described farmers as price takers and on the losing end of bargaining leverage against traders and disposers in Benguet. The social network analysis, in contrast, provides a more differentiated, holistic, and quantitative approach than has previously been explored for *sitios* in Benguet.

The key research questions this paper examines are: (1) How are social networks in Atok's upland communities structured; (2) Who are the most central farmers/households in the areas who can serve as influencers and who are the least connected who need to be reached by a different approach; (3) How effective has past extension work been as far as reaching the central actors is concerned; and (4) Can insights from the results be used for the design of information and education campaigns and other interventions in such areas?

Using social network analysis, we found that upland communities have varied social network densities and that network centrality is associated with the ability to move around and physical proximity to venues for social gathering. The paper further illustrates that past extension work has been effective to some extent, though improvements are needed to reach as many farmers as possible. The main contribution of this paper is its improvisation in harnessing knowledge from prevailing social structures to provide insights that may effectively improve the design of IECs and extension work in general.

The focus area of the study is the municipality of Atok in Benguet, a major source of high value crops. It is a fourth-class municipality with an area of 22,385.49 hectares. Two-thirds of the municipality is characterized as hilly to mountainous while the remaining one-third is rugged mountain areas. Most households depend on agriculture as their primary source of income. Most farms are rain-fed, with limited sources of supplemental irrigation. As mentioned earlier, there are only seven agricultural extension workers in Atok, including the municipal agriculturist, with each being assigned for extension work in each of these products — rice, corn, high-value crops, livestock, and potato production. However, it is expected that extension workers are also knowledgeable of crops outside their assigned crop or product. The municipal agriculturist and agricultural extension workers in the area described the difficulty of reaching smallholder farmers, which the latter similarly noted, because of limited modes of transportation, steep terrain, a poor road network and a lack of internet connectivity.

MATERIALS AND METHODS

This study uses primary data of 239 households from three communities in Atok. The study used a structured survey instrument administered through face-to-face interviews from October to December 2019. A full enumeration of the community (locally referred to as *sitio*, a cluster within a village) was required to have complete information about social networks. The study considered areas with relatively low constraint to complete enumeration and with existing census data of all households in the area.

Based on consultation with an academic partner and local officials, the study selected three *sitios* from Barangay Paoay and Cattubo, which are major producers of cabbage, carrots and potatoes. These were Proper Paoay in Barangay Paoay, and Tulodan and Macbas in Barangay Cattubo. Specifically, the sites together comprise 315 households, with 89 in Macbas, 94 in Tulodan and 132 in Proper Paoay. However, even though a full enumeration was ideal, there were substantial difficulties during the field survey, which prevented full enumeration. Based on the official list of households obtained from the local government, the total number of interviews expected was 315 households, but in the event, only 239 (119 in Proper Paoay, 74 in Tulodan, and 46 households in Macbas) were interviewed. Some of the respondents listed, but not interviewed, were no longer residing in the study sites. It was also difficult to schedule the interviews because of a very limited window for conducting the interview – which was either early in the morning, before the farmer went to the farm, or late in the afternoon after the farmer had returned home. The locations of the houses were also significantly far from each other, and some were in uphill areas that could only be reached by walking. These challenges resulted in the 76% response rate of the survey. Notwithstanding this, the data reflect at least 76% of the network connections and as such are already nuanced to provide an understanding about social networks of farming households in the upland communities of interest.

Note that all the sites are communities of 70–80% rain-fed vegetable farms, but with arguably varied potential for the spread of information. While Proper Paoay is a

Table 1. Economic profile and geographic constraints in the study areas.

	Brgy. Paoay *Sitio* Proper Paoay	Brgy. Cattubo *Sitio* Tulodan	*Sitio* Macbas
Accessibility from highway	Accessible	Less accessible	Least accessible
Terrain	Relatively less rough terrain than Cattubo	With steep/rough terrain	
Poverty rate, %	8.3	32.8	
Access to safe water, %	35	7	
Unemployment rate, %	0.2	1.9	

denser *sitio* in terms of population and nearer to the municipality, households in Macbas and Tulodan are more disperse and are located far away from the center of the municipality. Hence Proper Paoay is considered least rural among the three *sitios*. *Sitio* Tulodan, as a community, occupies a wider map area and thus seems more spread out, but closer inspection shows close clusters of households. It is these clusters of households that are in turn located relatively far from one another. On the other hand, the households in *Sitio* Macbas as a whole, live closer together within a smaller map area, but exhibit no clusters of households as in Tulodan, and have no dense hub of activities the way Proper Paoay does. *Sitio* Macbas and Tulodan are also more remote than Proper Paoay.

The demographics of each *sitio* also seem to differ. While *sitio*-level data on the socioeconomic standing of the communities is scarce, there is information from the Community Based Monitoring System (CBMS) that disaggregates data down to the barangay level. Per the 2014 –2017 CBMS, Barangay Paoay, where *sitio* Proper Paoay is located, experiences lower levels of poverty (8.3%) than Barangay Cattubo (32.8%), where *sitios* Macbas and Tulodan are located. Other indicators that Barangay Paoay is better off than Barangay Cattubo include greater access to safe water supply (~35% versus Cattubo's 7%) and access to sanitary toilets (96% against 81%). Both barangays have similar rates of children aged six to 15 not in school, both at close to 1%, while Barangay Paoay has a lower unemployment rate (0.2% against 1.9%).

Overall, these *sitios* are well-delineated based on geography and because they are of the same municipality, they are comparable with one another in terms of the cultural and political aspects. However, their differences in some other characteristics allow for a comparative analysis of social networks in the areas.

To obtain social relations data, the survey enumerator asked the respondents (household head and spouse, if any) to identify a maximum of 50 direct social contacts living within the same *sitio*, the physical boundary from which network information was gathered. To minimize interview fatigue and ensure that non-kinship relations were obtained, the inquiry was first made about friends and neighbors, then work-related links, and then relatives, and then information, peer-advice, and resource -sharing networks. Information on multiple networks, if any, was useful for better understanding social networks that can enhance information dissemination and other social influencing programs. Table 2 shows the different social links that were collected through the survey.

The network data were analyzed through social network analysis (SNA), a paradigm that focuses more on relations rather than attributes. SNA allows for analyzing the structure of ties which are said to influence constraints and opportunities that people face. SNA also provides a visual representation of the social linkages, a unique way of illustrating and understanding the social network structure. In contagion models, the higher the density (actual ties divided by the total number of possible ties) of the network (that is, more connections relative to total possible connections), the faster the rate of spread of a property like a disease (Banerjee et al. 2012). The theory of social influence also provides insights into social networks and their potential influence. This school of thought notes that social influence is a function of social proximity whether by structural cohesion (close social relation) or structural equivalence (having similar attributes or coming from a homogenous group).[3] Therefore, a more cohesive social network allows for more social influencing and greater diffusion of

Table 2. Social, economic and information networks gathered in the survey.

Friends and Neighbors	Work-Related	Kin	Other Social Networks
Close friends	Employer	Parent-child	Weather and climate information
Childhood friends	Worker	Siblings	Peer advice (farm-related
Neighbors	Co-worker, Colleague	Children	Resource/inputs (farm-related)
Kailian (kababayan)	Hired labor	Aunts/.Uncles	Credit links
Churchmate	Supplier	Cousins	Health infomation/ advice
	Creditor	Niece, nephew	
	Trader	Grandchildren	
	Disposer	In-laws	
	Trucker		
	Private technician		

[3] See Marsden and Friedkin (1994).

information. Social cohesion is operationally defined as the extent to which people within a community share resources and have trust in each other.

One objective measure for social cohesion is network density. If one seeks to disseminate information or influence people, it is likely to be more challenging for a more diffuse or less dense network, all else being equal. A more closely bonded community, on the other hand, would be more conducive for knowledge diffusion and social influencing among its members. Individual connectedness or centrality is also important. Network actors who have more connections are in a better position to receive and share information than those who have very few connections or are not connected at all (Jackson et al. 2016).

The software package developed by Borgatti et al (2002) called UCINET, was used to analyze the network and yield network parameters such as density, components (number of distinct clusters), geodesic distance (the length of the shortest path between any pair of network actors), and diameter (the shortest distance between the two most distant actors in the network). It also calculates, at the individual network actor level, parameters of connectedness such as degree, betweenness, closeness, 2-step reach, and eigenvector centrality, among others. Each parameter measures a specific aspect of connectivity. The degree gives the total number of nodes or actors which an actor of interest is directly connected to. The 2-step reach centrality is the number of actors one can reach in two or less steps; it provides the extent of an actor’s indirect links. Betweenness, meanwhile, is the proportion of pairs of actors for which a particular actor acts as a broker because that actor lies within their shortest path. Removing an actor with a high betweenness score is likely to lead to disruption of the channels of communications. The eigenvector centrality simply shows how central an actor’s connections are. Closeness centrality measures how close one is to all other actors in the network.

Identifying centrality is essential because it gives a notion of the hubs, the potential influencers and bridges that bind communities together (Jackson et al. 2016). These bridges are also potentially the most effective information disseminators and influencers. If information is coursed through them, it is expected that they can disseminate it more efficiently. Similarly, this analysis also provides the nodes at the periphery – that is, those who are least connected than the rest, and their characteristics. These people/households may benefit from a more direct approach to information dissemination because they have fewer connections.

Fig. 1. Map of Luzon, with Benguet pinned (left) and Benguet province and its municipalities (right).

The study provides the network graph for each of the selected sites, and by type of networks (social networks, information networks). The node in each graph pertains to a household. A line denotes the presence of at least one link between any two households. Attributes of actors or households have also been reflected in the network graphs for more nuanced appreciation. Examples of these are networks that show, through node coloring, the households which have interacted with an extension worker. The node size can also be differentiated based on centrality scores. It is important to note that this paper does not account for how networks are formed, nor is it about the causal relations between social connectivity and access to information. All analyses are exploratory and correlational.

Simple Ordinary Least Squares (OLS) regression models were estimated to determine the correlates of centrality. The dependent variables are various network parameters calculated through the UCINET based on social ties of the households. We selected only the parameters with a distribution that is near-normal for degree, closeness, and 2-step reach centrality. An index for connectivity was also developed via Principal Components Analysis (PCA) out of several network parameters. The explanatory variables, meanwhile, comprise demographic (age and years of education of the head, number of household members) and economic variables-asset indices (calculated through PCA involving basic phone, smartphone, tractor, water pump), house and vehicle ownership. Farming characteristics such as the area of farmland operated, the number of years spent in farming by the head, and exposure to outside financial resources proxied by availing credit ever were also included. A variable that controls for geographic constraints that can potentially impede a person’s ability to interact with many people was also included in the models. This pertains to the distance (in kilometers) from

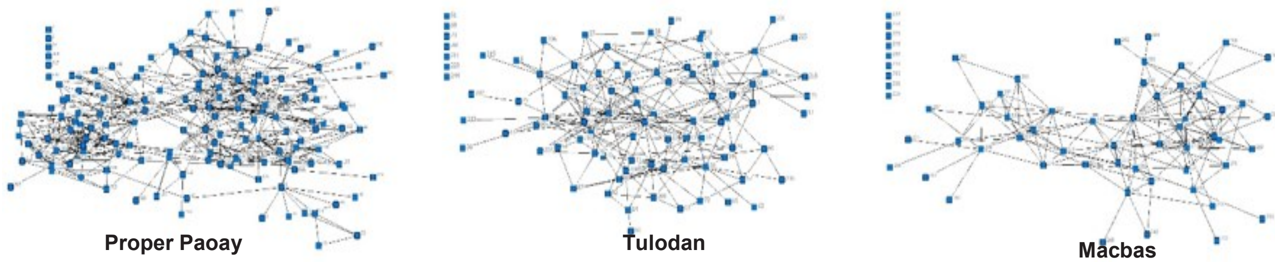

Fig. 2. Network graphs of inter-household social and economic relations by *sitio*.

the respondent's dwelling to a place frequently visited by the respondent – for instance, a market or church, etc. The summary statistics of the different variables are shown in Table 3.

Table 3. Summary statistics in regression estimations, household level.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Dependent variables					
Degree	228	0.0944	0.0677	0.006	0.426
2-Step reach	228	0.4463	0.2066	0.039	0.933
Closeness	228	0.3832	0.0683	0.225	0.598
Connectivity index	228	0.0056	2.3433	-4.612	8.838
Individual characteristics					
Age of head, in years	229	43.2149	14.5114	19.023	84.019
Age of head, squared	229	2077.183	1370.63	361.859	7059.22
Years of education of head	225	8.2756	3.4582	0	16
Being Kankanaey (1 – Yes, 0 – No)	228	0.6842	0.4659	0	1
Years in farming by head	228	17.1974	13.4302	0	57
Household characteristics					
No. of household members	229	3.9039	2.4079	1	20
Vehicles owned, number	229	0.4672	0.8455	0	5
House ownership (1- Yes, 0 - No)	228	0.7193	0.4503	0	1
Size of farm operated (hectares)*	229	37.1481	132.114	0	800
Ever availed credit (1 - Yes, 0- No)	229	0.4847	0.5008611	0	1
Asset index (predicted score via Principal Components Analysis)	228	0.0022	1.310644	-1.613	4.497
Distance to place frequented (km)	229	3.969	13.883	0	120

*This average size of farm operated by households in the sample includes 20 observations with responses of 100 ha and above.

RESULTS AND DISCUSSION

The structure of farming household networks in the three *sitios* varies. The network graphs in Figure 2 reflecting mainly the social and economic links among households shows that in each *sitio*, there is one big main component which means that except for the isolated ones, most households are connected. It also appears that there are more connections in Proper Paoay, the least rural and most accessible of the three *sitios*, while there are relatively fewer connections in Macbas than the other two *sitios*. These are so because Proper Paoay is the largest in terms of nodes while Macbas has the least number. Based on objective network parameters, *Sitio* Macbas, however, is considered the most cohesive among the three while Proper Paoay is the least cohesive based on density and average geodesic distance (Table 4). Macbas' density of 0.086 means that 8.6 percent of the total expected connections can be observed; Proper Paoay has only 0.044 and Tulodan has 0.061. The average geodesic distance of Macbas is roughly 2.8, which is quite similar to Tulodan's 2.86 and lower than Proper Paoay's 3.3. This means that on the average, households in Macbas and Tulodan are socially closer or more proximate with one another when compared to those in Proper Paoay. It can be noted, though, that Proper Paoay has a relatively higher average degree of direct connections than the others and that Macbas has more isolated nodes than the rest. This study likewise examined other types of networks such as farm advice and input networks, and information networks (specifically weather and climate information and health information). The pattern in the cohesion parameters is similar to that using the social (kinship and friendship) and economic (work-related) links among households.

These findings indicate that social cohesion can be understood based on the network parameters used. While density and distance are important measures, the presence of many isolated nodes is also crucial as far as designing information and education programs and other development efforts that require social influencing among people in rural areas. The relatively remote areas, Macbas

Table 4. Whole network parameters indicating social cohesion by type of network and *sitio*.

Measure	Social and Economic	Information (weather and climate)	Farm Advice/ Inputs	Health Information
Sitio Proper Paoay (no. of nodes=155)				
No. of ties	1054	1128	1020	860
Ave. Degree	6.8	7.277	6.581	5.548
Density	0.044	0.047	0.043	0.036
Ave. Distance	3.322	3.155	3.288	3.461
Diameter	7	7	7	9
Sitio Tulodan (no. of nodes=90)				
No. of ties	486	754	596	616
Ave. Degree	5.4	8.378	6.622	6.844
Density	0.061	0.094	0.074	0.077
Ave. Distance	2.858	2.47	2.684	2.746
Diameter	6	5	5	7
Sitio Macbas (no. of nodes=63)				
No. of ties	334	476	408	448
Ave. Degree	5.302	7.556	6.476	7.111
Density	0.086	0.122	0.104	0.115
Ave. Distance	2.779	2.464	2.606	2.468
Diameter	6	5	6	5

and Tulodan, are shown to have better cohesion scores than the more accessible Proper Paoay. This can be attributed to the remoteness of Macbas and Tulodan which means they are not likely to attract in-migrants, resulting in a closely-knit community made up of related households. On the other hand, Proper Paoay, which is more accessible and has relatively greater economic activity than the other two *sitios*, is most likely to attract people from other areas, which tends to make social relations, as a whole, less cohesive. However, the two *sitios* of Cattubo also have more isolated households than Proper Paoay, which likely reflects the significant constraints on mobility and social interaction due to the rough terrain and large distances between dwellings. Crucial to understanding network structure is identifying the characteristics of central actors. For this, an OLS model was estimated with the centrality score as the dependent variable. The regression results in Table 5 show that not many of the explanatory variables are significantly related to centrality when other factors are held constant. None of the individual characteristics matter, not even educational attainment, or ethnicity. The consistently significant variable is the number of vehicles which is expected given the substantial constraints to mobility. It can be argued that people who ferry products and people from the area to other places are relatively more popular or can interact often with other people.

House ownership seems to associate with having more direct links (degree) but does not significantly correlate with other centrality parameters. Interestingly, the more well-off households, as shown by asset index, are less likely to have high node centrality, based on this sample of upland communities. Perhaps this is because their need for social support from others is much lower than people who are less endowed. This is important evidence as it does not provide support for programs that select relatively wealthy people as information hubs, though this suggestion is based on this study's limited sample.

As expected, being far from venues where people can interact with one another is negatively correlated with

Table 5. Regression results by parameter, all *sitios*.

Variable	Degree		2-Step Reach		Closeness		Connectivity Index	
Individual characteristics								
Age of head, in years	0.00454	*	0.01498	*	0.0041767	*	0.16063	*
Age of head, squared	-0.00004		-0.00013	*	-3.40E-05		-0.0013	
Years of education of head	-0.00137		0.00254		0.0003599		0.0106	
Being Kankanaey (1- Yes, 0-No)	0.01012		0.05166		0.0198346		0.25735	
Years in farming by head	-0.0006		-0.00178		-0.0006971		-0.01904	
Household characteristics								
No. of household members	0.00324		0.01022		0.003569		0.08983	
Number of Vehicles owned	0.01749	**	0.05876	***	0.0202766	***	0.67442	***
House ownership (1- Yes, 0-No)	0.02714	*	0.05256		0.0230483		0.41831	
Size of farm operated (in hectares)	0.00003		0.00009		2.90E-05		0.00137	
Ever availed credit (1- Yes, 0-No)	0.00008		0.03922		0.0110176		0.0174	
Asset index (Predicted score via Principal Components Analysis)	-0.01069	**	-0.05047	***	-0.0155509	***	-0.40609	**
Distance to place frequented (km)	-0.00064	*	-0.00224	*	-0.0007685	**	-0.02422	*
Constant	-0.04473		-0.08148		0.2256361	***	-5.1012	**
R2	0.23		0.2758		0.2904		2084	
N	224		224		224		224	

centrality. The most central households are those situated near areas of congregations. It can therefore be noted that those in the network's periphery are people who also live in even more remote areas. There is another interpretation to this result. Since the place people frequently visit differs across households, those who frequently go to farther places are relatively less central than those who just move within the *sitios*. Those who travel to the city center and to even farther trading posts have fewer chances to interact with the local population and are therefore less known by others in the *sitio*.

Table 6. Mean centrality scores by type and group, all *sitios*.

Variable		Obs	Degree	Closeness	2-Step Reach	Centrality Index
Interact with government agricultural extension worker	Yes	130	0.0941	0.3211	0.3665	0.4986
	No	231	0.0779	0.3057	0.3151	-0.1279
T-test (*P*-value)			**0.0109**	**0.0038**	**0.0043**	**0.0032**
Attended LGU meetings	Yes	157	0.0857	0.3087	0.3377	0.1836
	No	234	0.0784	0.3069	0.3177	-0.1232
T-test (*P*-value)			0.2246	0.7453	0.2529	0.1324
Attended farm field school	Yes	96	0.0986	0.3277	0.4015	0.7512
	No	286	0.0778	0.3045	0.3086	-0.1587
T-test (*P*-value)			**0.0023**	**0.0001**	**0**	**0.0001**

Based on the regression analysis, we summarize the profile of central households or actors in upland communities as follows: (1) people who live near venues of social gathering such as village government hall, church, and market; proximity to these areas enables people to interact more with others within an extremely challenging physical environment; and (2) those who possess greater means of transport which is essential for people to navigate the area. Naturally, people who come from the largest clans would also be more central than others, holding other factors constant, because they are more likely to extend their reach to their relatives.

Apart from examining the network structure and central actors, this study aimed to illustrate how social network analysis can also aid in assessing the extent of the reach of agricultural extension workers for purposes of crafting more effective strategies in the future. There is some evidence that government extension worker (AEW) penetration has been quite effective in the past — as far as selecting people who are more central than others (Table 6). Survey respondents who have ever met an extension worker in the past tend to have statistically higher centrality scores than those who have not met any. This is also the case for those who have attended farm field school. On the contrary, those who have attended LGU meetings are not statistically different from those who have not attended such meetings in terms of relative position in the community.

When examined in more detail at the *sitio* level, however, the statistically higher mean scores between those who have interacted with AEW is only observed in Proper Paoay. This higher average score is also observed for those who have attended LGU meetings and farm field school compared to those who have not in the same *sitio*. This is not the case in Macbas at all. The attendees of LGU meetings in Macbas have statistically lower centrality scores than those who were non-attendees. The other groups are not statistically different from one another based on centrality scores. In Tulodan, the attendees of farm field school are more central than those who have not attended farm field school. Again, there are no statistically significant differences between the other groups in terms of relative position in the community networks. There is a need to improve on the penetration of extension workers and other LGU staff/officials in remote areas like Macbas and Tulodan (Table 7).

To gain some notion on how AEW (particularly government extension workers who have the mandate for information and education campaigns) penetration can be improved, we examined the spread and position of households who have interacted (through at least one member) with an AEW in the past through network graphs. The graphs below pertain to the network of kinship and friendship by *sitio*. There are isolated nodes which means that they do not share such relation with actors in the community. The red nodes are those who have interacted with AEWs in the past (we call these extension workers' initial contacts), light blue ones have not, white circle nodes are those which we failed to interview but were tagged by respondents as part of their advice network. The size of the nodes is proportional to their degree of centrality. The bigger the node the more central it is. It would be ideal if the red nodes were also the biggest nodes, which means that AEWs have succeeded in selecting or targeting central actors in their field visits and other interactions. It would also be ideal to see red nodes scattered throughout the network — this would mean that the selection was made in an even manner so that if we used them as information hubs, we would likely reach a broader segment of the population, all else being equal.

For Proper Paoay, regardless if it was intentional for AEWs to target central actors or not, the initial groundwork has been quite effective because AEWs have

Table 7. Mean centrality scores by type, group, and *sitio*.

Variable		Obs	Degree	Closeness	2-Step Reach	Centrality Index
Proper Paoay						
Interact with AEW	Yes	43	0.0965	0.3181	0.3243	0.3463
	No	132	0.0628	0.296	0.2578	-0.6635
T-test (*P*-value)			**0**	**0.0046**	**0.003**	**0.0003**
Attend LGU meetings	Yes	46	0.085	0.3122	0.3047	0.084
	No	137	0.0649	0.2971	0.2608	-0.6215
T-test (*P*-value)			**0.0108**	**0.0457**	**0.0446**	**0.0099**
Attend farm field school	Yes	24	0.0835	0.3181	0.3245	0.1325
	No	159	0.0679	0.2983	0.2639	-0.5312
T-test (*P*-value)			0.1256	**0.0409**	**0.0306**	0.06
Macbas						
Interact with AEW	Yes	20	0.1331	0.3195	0.4468	1.3118
	No	42	0.1299	0.3091	0.426	1.0789
T-test (*P*-value)			0.8681	0.3929	0.6293	0.6869
Attend LGU meetings	Yes	40	0.0895	0.2787	0.3182	-0.1551
	No	39	0.1353	0.3106	0.4385	1.2014
T-test (*P*-value)			**0.0064**	**0.0204**	**0.0056**	**0.0113**
Attend farm field school	Yes	20	0.1258	0.321	0.4565	1.1563
	No	50	0.1249	0.3024	0.403	0.8847
T-test (*P*-value)			0.9639	0.1491	0.2287	0.6386
Tulodan						
Interact with AEW	Yes	67	0.0809	0.3236	0.3696	0.3537
	No	57	0.0744	0.3255	0.3662	0.2234
T-test (*P*-value)			0.513	0.8419	0.9176	0.7248
Attend LGU meetings	Yes	71	0.084	0.3233	0.37	0.439
	No	58	0.0719	0.3275	0.3709	0.1632
T-test (*P*-value)			0.2156	0.658	0.9756	0.4444
Attend farm field school	Yes	52	0.095	0.3348	0.4159	0.8809
	No	77	0.0674	0.3187	0.3397	-0.0672
T-test (*P*-value)			**0.005**	0.0909	**0.0175**	**0.0087**

already been in touch with more central actors in the area as shown by Figure 3. If we focus on the biggest nodes, many of them are indeed red. Figure 3 also somewhat shows that so far, we can see red in most parts of the network. At least, these are not concentrated in a particular segment of the graph. The AEW penetration in Proper Paoay, therefore, appears to have been effective as far as the criteria mentioned above are concerned. The work therefore must proceed by encouraging these individuals to serve as extension aides or social influencers in disseminating information to other actors, particularly the peripheral ones. A good complementary strategy is to assign local information hubs among those in the periphery and have these hubs frequently monitored by the local government.

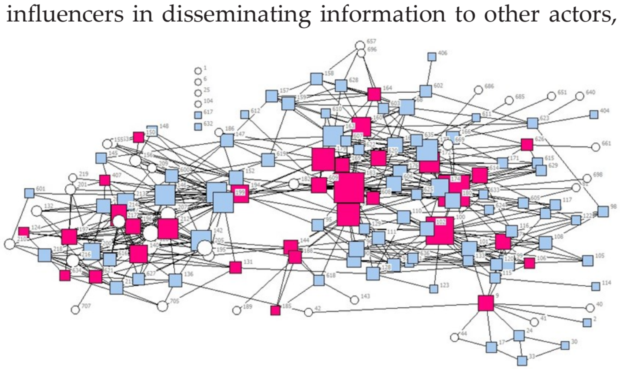

Fig. 3. Graph of social relations in Proper Paoay (red – with interaction with AEW in Atok), node size by degree.

Meanwhile, the situation in Tulodan appears to be that they have worked with more peripheral actors than did Proper Paoay. The red isolated nodes and red pendants (the nodes connected to the graph through just one link) illustrate this. Also, some red nodes are relatively bigger, which means that the LGU has targeted some central actors. It is, however, noticeable that the big reds are not necessarily bigger than the big light blue ones, though there is undoubtedly more even spread of the red in this graph than in Proper Paoay. This means that AEWs may not have succeeded in making initial contact with central nodes, but the promising part is that the spread of households which have been covered by AEWs is relatively dispersed. These households can therefore be good candidates for social influencers in the area (Figure 4).

In Macbas, Figure 5 shows that some red nodes are quite well-connected as shown by their bigger sizes.

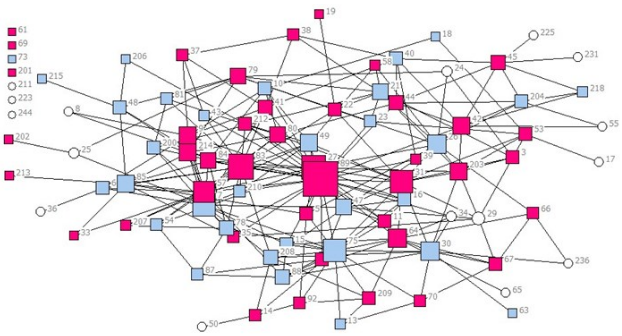

Fig. 4. Graph of social relations in Tulodan (red – with interaction with AEW in Atok), node size by degree.

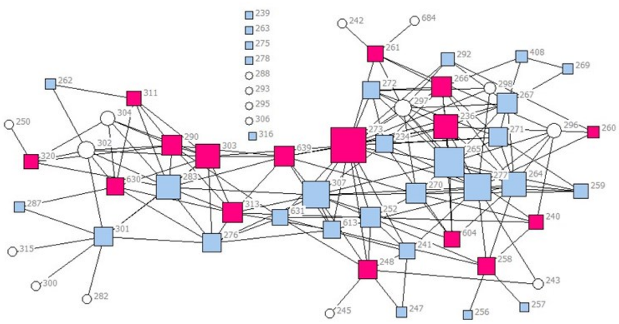

Fig. 5. Graph of social relations in Macbas (red – with interaction with AEW in Atok), node size by degree.

However, it shows that most of these households are directly linked to one another as shown by the red nodes sitting in some distinct segments while there are some parts of the network that do not have red nodes among them. Perhaps because Macbas is very remote, farm visits may have been done in pockets of related households. This points to the need for a more representative approach in conducting farm visits, presentations, and meetings by government extension workers. AEWs can improve on their work by identifying the central actors in those segments and encouraging them to echo the information they obtained. We can also see that some initial contacts are located at the periphery, which is promising because these can serve as hubs in their areas. This is better than not having any red at all among the nodes located at the periphery. Hence, the worst that we can expect, apart from not seeing any red in the graphs, is that if the reds are mostly the smallest nodes which means that they are not good candidates for relaying information, as they have very few connections. We can also see that AEWs need to work harder in Macbas to reach the isolated nodes. These visual analyses have enriched our understanding by showing the de-facto outcome of AEWs' efforts to reach households in the area and are instrumental in devising relevant strategies for improving AEWs' penetration.

CONCLUSION AND RECOMMENDATIONS

Based on the primary data gathered from Atok, Benguet, we found a varying extent of social cohesion possibly based on physical context. Consistent with expectation, remote communities are relatively more socially cohesive based on density and average geodesic distance. We found, however, that density is not a perfect measure of cohesion; there is a need to pay attention to isolated nodes, especially in upland rural communities. Contrary to expectations that there would be clusters, even communities near the population center can be connected, albeit with a low density, suggesting opportunities for social influencing and more fluid information dissemination.

Physical proximity and mobility are likely to be the key determinants of centrality within the community network in the context of significant geographic constraints. Central actors are those living near venues of interaction and those with greater means of transport. Peripheral ones are those who live far from these venues or those who travel long distances to market their goods and do not have means of transport. The most affluent families are not necessarily the most central actors; in fact, these households appear to be on the periphery (they may find less need for social support or are too preoccupied for social interaction). It would be interesting to see if such can also be said about other contexts in the Philippines. If so, practices that rely on approaching the economic affluent in communities for information dissemination may need to be re-examined.

Based on the results of this study, there may be a need for crafting different IEC approaches for different social and physical contexts. There is a need to promote more direct links (promote interaction) between central actors, the LGU, other information sources and producers, as well as promote activities that facilitate greater and more meaningful interactions among farmers — to stimulate social learning and influencing. Complementing these strategies with those that use knowledge from other research works may be useful as well. It is therefore recommended that AEWs and other stakeholders do partner with these potentially influential actors in relevant initiatives.

For a more detailed IEC strategy, AEWs and other partners must take advantage of areas that are visited frequently by residents as these are good candidates for convening people for information campaigns. For areas near population centers (still in the upland community's context) —the more immediate concern for AEWs and other stakeholders is how to incentivize their initial contacts to become disseminators of information within their networks. For more remote areas, the immediate focus may be the identification of central actors. Because of the remoteness of some areas, the AEWs' reach may be limited to some clusters, missing other segments. It is important to gather a set of participants that includes the other segments which may be overlooked in earlier efforts. Once these have been identified, they can be incentivized to act as information hubs for their networks. It is also important that AEWs make more direct interaction with people in remote areas.

Different communities have different structures and social norms and these differences must be accounted for in the design of IECs and other interventions aimed to promote social influencing and learning. Given that social network mapping is not always feasible and may not always be necessary, there are factors, from this paper, which help us gain some notion about such characteristics. IEC designs must account for social norms which are associated with physical characteristics of the area, the socioeconomic profile, availability, and accessibility of venues of congregation or interaction. It would be useful if future research can replicate this analysis in other regions to see if the results are similar.

ACKNOWLEDGEMENT

The authors would like to acknowledge the assistance of Benguet State University in the selection of study sites, the hiring of enumerators and the conduct of the survey in Atok, Benguet. Their expertise in the area is greatly appreciated. The authors would also like to thank the Philippine Institute for Development Studies for their support of the research. Further gratitude goes to the Australian Center for International Agricultural Research (ACIAR) and South Australian Research and Development Institute (SARDI) for funding and supporting this research endeavor.

REFERENCES CITED

BANERJEE A, CHANDRASEKHAR AG, DUFLO E, JACKSON MO. 2012. The diffusion of microfinance. National Bureau of Economic Research Working Paper 17743. Retrieved from https://www.nber.org/papers/w17743.pd.

BEAMAN L, DILLON A. 2018. Diffusion of agricultural information within social networks: Evidence on gender inequalities from Mali. Journal of Development Economics 133: 147–61. https://doi.org/10.1016/j.jdeveco.2018.01.009.

BORGATTI SP, EVERETT MG, FREEMAN LC. 2002. Ucinet for windows: software for social network analysis. Harvard, MA: Analytic Technologies. Retrieved from https://sites.google.com/site/ucinetsoftware/home.

CADGER K, QUAICOO A, DAWOE E, ISAAC M. 2016. Development interventions and agriculture adaptation: A social network analysis of farmer knowledge transfer in Ghana. Agriculture 6 (3): 32. https://doi.org/10.3390/agriculture6030032.

DECLARO-RUEDAS MYA. 2019. Technology transfer modalities utilized by agricultural extension workers in organic agriculture in the Philippines. Journal of Agricultural Extension 23(3). https://dx.doi.org/10.4314/jae.v23i3.6.

DOMINGO SN, AGBON AD, OLAGUERA MD, UMLAS AJL, ZULUAGA KMC, REYES CM. 2020. Barriers to application of weather and climate information in smallholder vegetable farming in Benguet.

HOANG LA, CASTELLA JC, NOVOSAD P. 2006. Social networks and information access: Implications for agricultural extension in a rice farming community in Northern Vietnam. Agriculture and Human Values 23 (4): 513–27. https://doi.org/10.1007/s10460-006-9013-5.

ISAAC M, ERICKSON B, QUASHIE-SAM S, TIMMER V. 2007. Transfer of knowledge on agroforestry management practices: The structure of farmer advice networks. Ecology and Society 12(2). Retrieved July 13, 2020, from www.jstor.org/stable/26267879.

JACKSON MO, ROGERS BW, ZENOU Y. 2017. The Economic consequence of social-network structure. Journal of Economic Literature 55(1): 49-95 https://doi.org/10.1257/jel.20150694.

KHALID SMN, SHERZAD S. 2019. Agricultural extension manual for extension workers. Food and Agriculture Organization (FAO) of the United Nations. Apia.

MARSDEN PV, FRIEDKIN NE. 1994. Network studies of social influence. In S. Wasserman & J. Galaskiewicz (Eds.), Advances in social network analysis (pp. 3–25). Thousand Oaks, CA: Sage. http://dx.doi.org/10.4135/9781452243528.n1.

MAGUIRE-RAJPAUL V, KHATUN K, HIRONS MA. Agricultural information's impact on the adaptive capacity of Ghana's smallholder cocoa farmers.

Retrieved March 17, 2020. https://www.frontiersin.org/articles/10.3389/fsufs.2020.00028/full.

MILAGROSA A AND SLANGEN LHG. 2006. Measuring social capital among indigenous agricultural people of the Cordilleras in Northern Philippines. 2006 Annual meeting, July 23-26, Long Beach, CA 21126, American Agricultural Economics Association (New Name 2008: Agricultural and Applied Economics Association). Retrieved from https://econpapers.repec.org/paper/agsaaea06/21126.htm.

NIDUMOLU U, LIM-CAMACHO L, GAILLARD E, HAYMAN P, HOWDEN M. 2018. Linking climate forecasts to rural livelihoods: Mapping decisions, information networks and value chains. https://www.sciencedirect.com/science/article/pii/S2212094716300159.

PRATIWI A, SUZUKI A. 2017. Effects of farmers' social networks on knowledge acquisition: Lessons from agricultural training in rural Indonesia. Journal of Economic Structures 6(1). https://doi.org/10.1186/s40008-017-0069-8.

RAMIREZ A. 2013. The influence of social networks on agricultural technology adoption. Procedia – Social and Behavioral Sciences 79: 101–16. https://doi.org/10.1016/j.sbspro.2013.05.059.

REYES CM, DOMINGO SN, AGBON A and OLAGUERA MD. 2017. Climate-sensitive Decisions and Use of Climate Information: Insights from selected La Trinidad and Atok, Benguet Agricultural Producers. Philippine Institute for Development Studies Discussion Paper Series No. 2017-47. Retrieved from https://think-asia.org/bitstream/handle/11540/7863/pidsdps1747.pdf?sequence=1.

RUSSEL SD. 1987. Middlemen and moneylending: relations of exchange in a highland Philippine economy. *Journal of Anthropological Research* 139-161.

SPIELMAN DJ, DAVIS K, NEGASH M, AYELE G. 2010. Rural innovation systems and networks: Findings from a study of Ethiopian smallholders. Agriculture and Human Values 28(2) (June): 195–212. https://doi.org/10.1007/s10460-010-9273-y.

VISHNU S, GUPTA J, PADMAJA SS. 2020. Diversity, complexity, and structure of social networks: Study of a smallholder dairy project. Outlook on Agriculture, 49(3): 245–255. https://doi.org/10.1177/0030727019893100.

VILLANUEVA AB, OGWAL-OMARA R, JHA Y, WELCH EW. 2016. Influence of social networks on the adoption of climate smart technologies in East Africa: Findings from two surveys and participatory exercises with farmers and local experts. https://www.researchgate.net/publication/306324102_Influence_of_social_networks_on_the_adoption_of_climate_smart_technologies_in_East_Africa_Findings_from_two_surveys_and_participatory_exercises_with_farmers_and_local_experts.

WOOD BA, BLAIR HT, GRAY DI, KEMP PD, KENYON PR, MORRIS ST, SEWELL AM. 2014. Agricultural science in the wild: A social network analysis of farmer knowledge exchange. PLoS ONE 9 (8). https://doi.org/10.1371/journal.pone.0105203.

WOSSEN T, BERGER T, MEQUANINTE T, ALAMIREW B. 2013. Social network effects on the adoption of sustainable natural resource management practices in Ethiopia. International Journal of Sustainable Development & World Ecology 20(6): 477–83. https://doi.org/10.1080/13504509.2013.856048.