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Analyzing the Resilience of Farming Households in Upland Areas

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Abstract

The challenges faced by farming communities, such as typhoons, floods, droughts, volcanic eruptions, and pest infestations, can pose significant costs on their livelihoods. This study examines the resilience of upland farming households using a small yet novel survey conducted in the municipality of Atok in Benguet. To analyze resilience, the study explores indicators based on the conceptual framework put forward by Schipper and Langston (2015), namely learning, options, and flexibility. Principal Components Analysis (PCA) was applied for index creation, while ordered logistic regression was employed to assess recovery levels of farming household. The findings show that factors contributing to the learning dimension of resilience include wealth/assets, strategic positioning within social networks, and access to transportation, proxied by vehicle ownership. The study recommends targeted interventions for households in lower-income brackets, peripheral network positions, and those lacking their own means of transportation, especially focusing on enhancing learning capacities.

Keywords: Resilience, upland farming, recovery, agricultural sector

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Analyzing the Resilience of Vegetable Farmers in Upland Areas

Aubrey D. Tabuga, Anna Rita P. Vargas, and Madeleine Louise S. Baiño

1. Introduction

The agricultural sector in the Philippines faces a variety of environmental, economic, social, and institutional risks. Being in the Pacific Ring of Fire and along the Pacific typhoon belt, the Philippines often experience different forms of natural disasters. In the Global Climate Risk Index 2021, the Philippines ranked fourth among countries most affected by extreme weather events from 2000 to 2019 after experiencing 317 weather-related events during the period (Eckstein et al. 2021). Due to typhoons, flash floods, drought, volcanic eruption, pest infestation, disease outbreaks and fish kill, among others, the Philippine agriculture sector suffered from a PHP 19.38 billion production loss in 2021 (Department of Agriculture 2021). 72 percent or PHP 13.91 billion of the production loss were caused by Typhoons alone. Farming communities also face numerous risks that stem from volatile prices and changes in access to market, e.g., due to the community lockdown, shrinking farm sizes (FAO 2020), decline in labor (Briones 2017a), limited capital formation, and poor rural infrastructure (Llanto 2012).

The impacts of these challenges depend on the quality of the soil, cropping patterns, infrastructure on irrigation, flexibility of credit providers and supply chain partners, and availability of agricultural insurance (Diogo et al. 2017). Identifying the vulnerabilities in social-ecological systems by assessing a farming communities' resilience can reduce the impact of these vulnerabilities and create a more sustainable future for people and the land. Agricultural resilience is the ability of the farming communities to absorb and recover from shocks to their agricultural production and livelihood. The growing importance of building resilience and adaptive capacity in rural communities is emphasized by authorities across the world.

This study examines the resilience of farming households in upland areas in the Philippines by specifically looking into the circumstances of predominantly vegetable growers in Atok, Benguet. The municipality of Atok is situated at the middle portion of the upland Benguet province. Upland areas are defined by the Philippine government as areas with slopes of 18 percent or higher. Atok's elevation is 1,780 meters above sea level. Due to their topography, upland areas are prone to erosion. According to the National Disaster Risk Reduction and Management Council (NDRRMC), Atok, Benguet is susceptible to destructive ground shaking and highly susceptible to rain-induced landslide and earthquake-induced landslide. Given that agriculture is highly sensitive to changes in climate, and Atok is the second largest producer of highland vegetables in the country, it is imperative to characterize and improve the resilience and adaptive capacities of its farming communities. The research questions this paper intends to inquire on are - What is the level of resilience among farmers in Atok? How can we improve the resilience of farmers in the upland areas?

2. Objectives

This study aims to assess the resilience of farmers in Atok, Benguet and recommend ways to improve it. Specifically, it explores and analyzes farmers' and their households' resilience against crises that may be caused by natural calamities and other shocks using the survey dataset collected for the ACIAR study involving 239 households (377 individuals) from Atok, Benguet in the 4th quarter of 2019. Employing the conceptual framework by Schipper and Langston (2015), this study intends to explore and develop indicators of household resilience, examine those who are 'least resilient' and provide insights on possible interventions.

3. Review of Related Literature

Holling (1973, p. 17) defined resilience as a "measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables." Several frameworks and indexes have been developed to measure resilience in social-ecological systems. Cabell and Oelofse (2012) developed an index of behavior-based resilience indicators for the agroecosystems. These indicators indicate enhanced capacity of the system to endure and effectively fulfill human needs for food, fuel, and fiber over the long term. The indicators compiled include Socially self-organized, ecologically self-regulated, appropriately connected, Functional and response diversity, optimally redundant, spatial and temporal heterogeneity, exposed to disturbance, coupled with local natural capital, Reflective and shared learning, globally autonomous and locally interdependent, Honors legacy, Builds human capital, reasonably profitable. The presence of these behaviors is crucial for the resilience of the agroecosystem, and their absence indicates vulnerability, signaling a requirement for intervention.

Meuwissen et al. (2019) developed a comprehensive resilience enabling framework for farming systems building on the concept of adaptive cycles and presented a methodology to operationalize the framework. The framework differentiates five phases. The first phase is characterizing the farming system by identifying the main product(s) of interest (Resilience of *what?*). The second phase is evaluating the key challenges that impact performance of the farm (Resilience to *what?)*. This phase considers environmental, social, and institutional challenges that farm communities face. The third phase is framing the essential functions of the system (Resilience *for what purpose?*). Farms provide multiple functions; they function as a provider of private goods by producing food and other resources or as a provider of public goods by maintaining natural resources. These functions may change overtime and transformation may be required. The fourth phase assesses resilience against the three categories of indicators, namely robustness, adaptability, and transformability (What r*esilience capacities?*). Robustness is defined as the capacity to withstand stresses and (un)anticipated shocks. Adaptability is the capacity to change production inputs, management of risks, and other activities in response to shocks. Transformability is the capacity to change the structure and feedback mechanisms in response to either severe shocks or enduring stress that make business as usual impossible. Lastly, identifying attributes of the farming system that enhances resilience (*What enhances* resilience?) in the context of the five generic principles of resilience as proposed by the Resilience Alliance (2010).

Defiesta and Rapera (2014) determined the levels of adaptive capacity of farming households 520 farming households in Dumangas, province of Ilo-ilo in the Philippines, to climate change, identified the factors that cause the differences in adaptive capacity and assessed whether adaptive capacity translates to adaptation. The authors used a composite index of adaptive capacity based on the sustainable livelihoods framework. The index included five indicators namely human resources, physical resources, financial resources, information, and livelihood diversity. Results showed that notwithstanding levels of adaptive capacity, majority of respondents adapt to climate change. However, more than half of the farming households have low adaptive capacity and only a meager 4 percent have high adaptive capacity. The authors find that the differences in adaptive capacity were caused by large disparities in information, physical and financial resources. Generally, farmers are able to adjust to changes in climate, regardless of their level of adaptive capacity, in order to survive and maintain their consumption. However, farmers who have higher levels of assets are able to adapt more effectively because they have access to a greater number of adaptation strategies.

Heckelman et al. (2018) presented an evaluation of climate resilience in both organic and conventional rice systems situated in four neighboring villages in Negros Occidental, Philippines. They employed the Self-evaluation and Holistic Assessment of climate Resilience of farmers and Pastoralists (SHARP) tool developed by the United Nations Food and Agriculture Organization. This tool measured 13 agroecosystem indicators of climate resilience and examined the influence of household, farm, and community mechanisms on adaptation capacity, mitigation potential, and vulnerability. The study adopted a participatory approach to contextualize these indicators within the socioecological setting, aiming to identify specific interventions for enhancing climate resilience based on local farmer experiences and socio-ecological condition. A participatory approach is employed to situate these indicators in their socio-ecological context and identify targeted interventions for enhancing climate resilience based on local farmer experiences and socio-ecological conditions. Results of the study show that most of the indicators suggest that organic rice systems are overall more climate resilient than their conventional counterparts.

The review of the scholarly works shows that there is dearth of studies done on the resilience of upland farming communities in the Philippines. Given the huge significance of the agricultural products that come from upland areas like Atok, Benguet to the Philippine market, there is therefore a great need to analyze the resilience of farming communities in such areas.

Resilience and Social Capital

Social capital is a significant factor in various types of households and community resilience to environmental shocks (Lyons et al., 1998; Adger, 2003). Social capital is defined by Robert Putnam (1993, p. 1) as "the features of social organizations, such as networks, norms, and trust, that facilitate action and cooperation for mutual benefit". It has been recognized as a crucial driver of sustainable disaster recovery. In times of disaster and during the recovery phase, social capital serves as a resource that frequently complements the efforts of local, regional, and national governments. According to literature, individual and community social capital networks offer access to diverse resources in disaster scenarios, including information, assistance, financial resources, childcare, as well as emotional and psychological support, as highlighted by Elliott, Haney, and Sams-Abiodun (2010), Hurlbert, Haines, and Beggs (2000), and Kaniasty and Norris (1993).

Aldrich and Meyer (2014), in their article on social capital and community resilience, presented empirical proof of social capital in disaster settings and categorized them into three types of social capital: bonding social capital, bridging social capital, and linking social capital. The first type of social capital is *bonding social capital*. This comprises the social ties linking people who share sociodemographic characteristics (Putnam, 2000). It describes the connections among individuals who are emotionally close, such as friends or family, and result in tight bonds to a particular group (Adler & Kwon, 2002). Through Bonding social capital, individuals can receive alerts, plan for potential disasters, find places to stay and resources, and access immediate assistance and initial support during a crisis (Hawkins & Maurer, 2010). During times of calamity, family connections play a crucial role in their resilience because relatives are typically the primary source of aid and support (Garrison & Sasser, 2009). Nakagawa and Shaw's (2004) study, as mentioned in Aldrich and Meyer's (2014) article, on the role of social capital in the rehabilitation and reconstruction programs after the earthquakes in Kobe, Japan and Gujarat, India uncovered that communities with high trust, norms, participation, and networks were able to recover from disaster more quickly.

Bridging social capital is another form of social capital which refers to connections between people who are not closely affiliated with each other but have links across different social groups based on factors like race or class. These connections are more likely to involve a diverse range of people and provide unique information and resources that can help individuals make progress in society. (Aldrich and Meyer, 2014). Ties with social organizations can provide support via institutional channels and offer opportunities to establish relationships with individuals who might not be reachable through bonding social capital. Bridging social capital is observed during the aftermath of Hurricane Katrina in the city of New Orleans in 2005. Mary Queen of Vietnam Church, a Vietnamese Catholic parish in New Orleans contributed to resilience of the Mary Queen of Vietnam community through charitable action by local and national organizations, which brought in external resources and commercial cooperation between businesses and community members that provided resources and labor (Airriess, 2008).

Linking social capital, the third type of social capital, that helps to establish connections between everyday individuals and those in positions of authority. This type of network embodies "norms of respect and networks of trusting relationships among people who are interacting across explicit, formal, or institutionalized power, or authority gradients in society" (Szreter & Woolcock 2004, p. 655).

Several studies have explored the complex relationship between social capital, human capital, and household and community resilience in different contexts. Anuradha, Fujimura, Inaoka, and Sakai (2019) focused on investigating the effects of social and human capital on household resilience in an agricultural village community in Sri Lanka that faces environmental stresses such as drought, crop raiding, and limited access to clean water. Their study found that bonding and bridging social capital, as well as economic activeness of human capital, were the key predictors of household resilience. Particularly, information sharing among neighbors, which is a manifestation of bonding social capital, played a crucial protective role against the environmental constraints faced by residents. Maintaining bridging social capital was identified as especially important for enhancing household resilience in the face of environmental stresses, more so than any other dimension of social and human capital.

Patel and Gleason (2017) explored ways to improve social cohesion and resilience simultaneously in urban communities to enhance disaster risk reduction efforts worldwide. Their study found a strong association between social cohesion and community resilience, indicating that social cohesion is a critical predictor of community resilience, regardless of demographic differences. Surprisingly, some underlying assumptions that factors such as income, time in the community, and education level have a positive relationship with resilience were countered by the research results. The study also found a non-linear relationship between social cohesion and resilience, suggesting that social cohesion has the most substantial impact on improving resilience at the community level in urban slums.

Carrico et al. (2019) investigated the impact of individual-level measures of cognitive and structural social capital on livelihood outcomes for smallholding rice farmers across six rice-farming communities in Sri Lanka. Their study found that the connection between social capital and resilience varies for different members of the community, and some members may have to make a difficult tradeoff between agricultural productivity and maintaining social relationships. The study concludes that social capital did not have the positive effects on agricultural and economic outcomes that prior research has suggested in the context of drought-affected rice farmers in Sri Lanka. While no main effects of social capital on livelihood outcomes were identified, the study highlights that the link between social capital and resilience operates differently for different members of the community. Therefore, it is crucial to account for heterogeneity when developing policies and programs that aim to improve livelihood outcomes by promoting social capital.

3.1. Principal Components Analysis as a tool in developing Resilience Indexes

Principal Components Analysis (PCA) is a method for reducing the number of variables in a dataset by transforming them into a smaller set of variables known as principal components. These components capture the majority of the variance present in the original variables (Laerd statistics, n.d.). This technique is used in several studies that developed indexes to measure resilience.

Tesso et. al (2012) determined magnitudes and patterns of rural households' vulnerability to climate change and at the same time identified the important determinants for resilience at household level in North Shewa zone of Ethiopia. The authors used an integrated vulnerability analysis methodology to construct indices for socioeconomic and biophysical indicators. These indicators were categorized based on adaptive capacity, exposure, and sensitivity to the impacts of climate change. PCA was used to compute vulnerability index of each agroecological zone. Probit regression was also used to identify and analyze the determinants of households' resilience to climate change induced shocks. Results of the study show that farmers residing in highland regions exhibited a higher vulnerability to natural shocks when compared to those in lowland areas. In addition, women headed household, families with high dependency ration, farmers operating on less fertile and steeply sloping farms and less diversified enterprises, are disproportionately affected by climate variability.

Asmamaw et al. (2019) used the Climate Resilience Index (CRI) to assess the households' resilience to climate change-induced shocks in Dinki watershed, northcentral highlands of Ethiopia. CRI is a "data-backed assessment that takes into consideration factors contributing to climatic vulnerability, existing adaptation mechanisms in place and ability of the system to bounce back in case of an adverse climatic event. The index thus measures the ability of a state to cope with climate risks" (Bhatia, 2021). To identify the determinant factors and indicators to household resilience, the authors employed PCA and multiple regression analysis, respectively. The findings indicate that the resilience of households to climate change-induced shocks is influenced by factors such as the accessibility and utilization of livelihood resources such as farmlands and livestock, livelihood diversification, infrastructure, social capital, and ecological stability.

Bunch et. al (2020) developed a resilience index in their study on quantifying community resilience in South Sudan. The three dimensions of the index, namely, (1) absorptive, (2) adaptive, and (3) transformative capacity was analyzed using PCA. The findings show that access to social capital and other positive strategies is crucial in absorptive resilience. The presence of programming such as education and training of farmers on good farming practices for conservation are linked to adaptive resilience. In addition, building community-level social capital enhances a household's transformative resilience since it allows households to have access to financial institutions, land, and agricultural inputs.

Jayadas and Ambujam (2021) assessed the Farmer Resilience Index (FRI), a village-specific resilience measure, by considering variables across four dimensions: economic, social, technical, and physical. This assessment aimed to reveal the resilience of farmers at the household level in two rural villages. The FRI draws its framework from the Climate Disaster Resilience Index developed by Joerin et al. in 2014 and 2012. The authors assessed the index with respect to two disasters namely Cyclone Thane (2011) and the South Indian floods (2015) which devastated Cuddalore district, Tamil Nadu, India. They developed a survey comprising dimensions, parameters, and variables to be presented to respondents in each farming household. Principal Component Analysis (PCA) was conducted for the variables within each dimension for each village individually to determine the respective weights. The findings show below-average physical resilience of farmers from both communities. This suggests that farming households undertake minimal measures to enhance their resilience, given that the majority of extension services and support come from governmental authorities. The study also reveals that encounters with cyclones and floods contribute to increased preparedness, driven by a learning effect that occurs after experiencing such events. Farmers with limited exposure to climate extremes have fewer disaster experiences and take a longer time to enhance their resilience. However, their ability to absorb and overcome shocks from disasters gradually improves as they consistently acquire knowledge about climate extremes and adopt corresponding adaptation measures.

Ramilan et. al (2022) quantified household resilience and identified livelihoods and their influence on resilience in the semi-arid tropics of India. There were four stages in the study's methodology: First, was the creation of the resilience capacity index, a multi-dimensional index developed by identifying key variables and their associated weights through PCA; Second, was a multifactor analysis used to derive livelihood strategies; Third, was the assignment of households to a livelihood strategy based on their highest factor score; And last, an application of regression analysis on the resilience capacity index as a dependent variable against the livelihood strategies to explain their influence on household resilience. The findings show that household resilience is strengthened by the possession of livestock, crop diversification, access to irrigation, and income diversification. The findings also show that access to credit promotes adoption of new technologies and enhances the risk-bearing ability of smallholder farmers.

The review of the scholarship shows that there is dearth of studies done on the resilience of upland farming communities in the Philippines. Given the huge significance of the agricultural products that come from upland areas like Atok, Benguet to the Philippine market, there is therefore a great need to analyze the resilience of farming communities in such areas.

4. Methodology

4.1. Conceptual Framework

To assess the resilience of upland farmers, this study intends to explore and identify indicators of farming household resilience. In the development of a resilience indicator, the study will employ the framework of Schipper and Langston (2015). The authors identified a set of criteria that encompasses key dimensions of resilience and are useful and flexible enough for use in various contexts. These key dimensions include learning, options, and flexibility.

Learning is characterized as the process of "gaining greater knowledge and awareness of risk or threats faced" (Schipper and Langston, 2015, p. 13), including the ability to incorporate lessons into preparedness and recovery for a resilient outcome (Djalante and Thomalla, 2010). It goes beyond merely knowing evacuation procedures, encompassing a deeper understanding of the implications of risk and community attitudes towards risk (Mayunga, 2006). Learning also entails the capacity to share information with others (Cabell and Oelofse, 2012) and discern reliable and useful information for preparedness and recovery purposes. It is essential for individuals to take action to diminish their exposure and sensitivity to climate change and natural hazards, contributing to the development of situational awareness (Rodin, 2013). This includes understanding changes in social, ecological, political, and economic circumstances (Gaillard et al., 2010). Beyond emergency preparedness, it necessitates comprehension of individual and collective strengths and weaknesses, coping options, and their limitations (IFRC, 2011a).

Being aware of weaknesses or limitations does not necessarily indicate that individuals possess the power or skills required to address them, particularly if certain groups are marginalized due to structural factors, historical biases, or ideological disagreements. Hence, individuals also require a large degree of *options*, enabling them to navigate factors driving vulnerability. This primarily involves having choices and alternatives to modify behavior, such as switching crops or seeds, exploring new income sources, or changing physical locations – all recognized as crucial resilience-building options (CARE, 2014; Thornton and Herrero, 2014; McGray et al., 2007). These options necessitate knowledge, entitlements, wealth, and access, representing fundamental enabling characteristics that link resilience to sustainable livelihoods, capacities, and capabilities (Keck and Sakdapolrak 2013). Utilizing such options can also involve support networks that genuinely offer altruistic assistance (Kennedy and King 2014). From these considerations, various components can be included to operationalize options, including wealth and assets, social capital, and knowledge.

Flexibility implies "the ability to withstand disruption without complete collapse, and to return to a functioning state as highlighted by the Resilience Alliance approach" (Walker et al., 2006 as cited in Schipper and Langston 2015, p. 14). Flexibility also implies the capability to recover from disruptions without incurring excessive costs or enduring prolonged periods (Obrist et al., 2010). Moreover, a crucial aspect of flexibility is a significant degree of self-regulation, indicating a low level of interdependence among different sensitive variables (Rodin, 2013, Cutter et al., 2010). This implies that in the event of flooding, people should still have the ability to travel in and out of their location (Berkes 2007), goods and services should continue without interruption, and crops produced in the area should not be lost due to a natural hazard, ensuring that the workforce can continue harvesting without interruption for emergency operations. It is important that "livelihood strategies should not be dependent on at-risk resources or institutional arrangements" (Schipper and Langston 2015, p. 14).

Learning, options and flexibility is crucial in supporting initiatives to foster resilience. Ultimately, the study aims to apply these principles in the creation of a resilience index.

4.2. Research Design

The study explores and develops some indicators of farming household resilience based on the conceptual framework put forward by Schipper and Langston (2015) which examined various systematic reviews about resilience. The study utilizes the primary data collected from the previous ACIAR study by Tabuga (2021) involving households from three sitios in the municipality of Atok in Benguet Province. The dataset includes the respondents' demographic and economic characteristics, their farming activities/employment characteristics, social networks, and memberships in organizations.

The indicators under each dimension are aggregated through Principal Components Analysis (PCA) to come up with indices of learning, options, and flexibility. The approach is based on the method of Jayadas and Ambujam (2021), discussed in the literature review. Jayadas et al (2021) developed a farmer resilience index (FRI) for climate disasters at the household level in coastal farming communities in southern part of India. Principal components analysis (PCA) was used to create dimension-wise resilience indices such that the study came up with economic resilience index, social resilience index, technical resilience index, and physical resilience index.

The weight for each respondent's score is determined based on the component loadings of the first principal component having an Eigenvalue greater than 1 and a higher percentage of variance (Filmer & Pritchett 2001; McKenzie 2005 as cited in Jayadas et al, 2021). The formula for the dimension-wise resilience index is as follows:

$$\text{Dimension-wise Resilience Index}_i = \frac{\sum_{j=1}^{n} (\text{Weightage} * \text{Variable score})_j}{n}$$

where i is the dimension (e.g., economic resilience index) and j is the number of variables under the corresponding dimension.

Implementing the abovementioned method, Jayadas et al (2021) found that marginal farmers – that is poor and those belonging to lower castes, have the lowest resilience. Specifically, 70 percent of the observations are considered marginal farmers who have the lowest FRI of 0.47.

This study will implement the same methodology, but the dimensions will be that in Schipper and Langston (2015) – learning, flexibility, and options. We have not found any study that has distinguished these three dimensions of resilience based on Schipper and Langston (2015) through principal components analysis (PCA). The advantage of looking at each dimension is for drawing useful and detailed insights on how to improve farming households' resilience. This is because we will understand the specific characteristics of households that are lacking in certain dimensions and such understanding will figure in the recommendations on how to enhance resilience among farming households in the upland areas. Table 1 shows some indicators available in the survey dataset that may be included in each of the three domains of interest.

Upon review, the list of expected variables included in each dimension was further reduced given some limitations in the dataset that was encountered. As mentioned in Tabuga et al. (2021), the survey experienced multiple issues which may have led to some unaccounted values. Moreover, a few of the initial variables identified were only applicable to select households as such these were also dropped from the domains. This resulted in the creation of a learning dimension and a combination of options/flexibility dimension.

In particular, the learning dimension includes important information of the household, as represented by the household head and their spouse, namely educational attainment, access to the internet, and receptiveness to advice proxied by being open to adopting new technology. On the other hand, the options/flexibility captures how assets and diversification of income sources can be used to recover from disasters, specifically looking at vehicle ownership, access to credits and other income sources, as well as number of different crops maintained.

Table 1. List of indicators considered in examining resilience and adaptive capacity of upland farmers.

Domain	Expected variable	Actual variables
Learning	Highest educational attainment of household head	HH head or spouse is at least high school graduate
	Active Search for Weather-related Information	
	Use Any of The Weather-Related Information in Farming Activities	
	Access to the internet	HH head or spouse has internet access
	Presence of Varied Sources of Information	

	Being Able to Access Information if needed (Typhoon & Rainfall)	
	Attendance in Farm Field School/Workshop	
	Engagement with Extension Worker	
	Member/Beneficiary of agriculture development programs and organization	
	Likelihood in Adopting New Technology	HH is highly likely to adopt New technology
Options	Other sources of income aside from farming	HH has other income source
	Availment of credit – proxy for access to credit	HH has availed credit ever
	Financing other farms	
Flexibility	House floor area in sqm - proxy for assets	House floor area in sqm
	Proportion of durable assets, number of durable assets	No. of vehicles owned by the HH
	Diversity in agricultural activities/Varied farming activities	No. of farm activities engaged by the HH
	Main source of water	
	List of channels used for marketing	
	Adopting technology or being open to adopting technology	
	Network position (measured by degree, closeness and betweenness)	

In addition, an evaluation done in relation to actual resilience exhibited during situations where households experience a disaster. The study employs a regression analysis to determine the resilience of households identified as vegetable farmers, specifically looking at upland areas. The dependent variable of the model is the complete recovery of farmers from shocks, specifically using the following questions in the survey: "Did any of the disaster events that you mentioned cause difficulty/problem that affected your household? As of now, has the household recovered?". Based on the above, households were given the option to answer whether they have completely recovered, partially, and not at all. As such, the study uses an ordinal regression with the highest rank given to fully recovered households and last to those households that have not recovered. In terms of independent variables, the indicator created from learning, options, and flexibility including other socioeconomic characteristics were used.

5. Results and discussion

5.1. Profile of respondents

The respondents from the survey done by Tabuga et al. (2021) came from households residing in Atok, Benguet. In particular, the survey took a total of 239 household sample with 396 individuals in Barangay Paoay and Barangay Cattubo (see Table 2). For each household, only the household head and the spouse were interviewed. In this case, the individuals are assumed to represent their respective household and are the primary decision-makers. As such it is important to understand basic information about the individuals leading the household. Since not all of them are married, with three out of ten being single, divorced, widowed, or with live-in partners, the study focused on profiling the household heads.

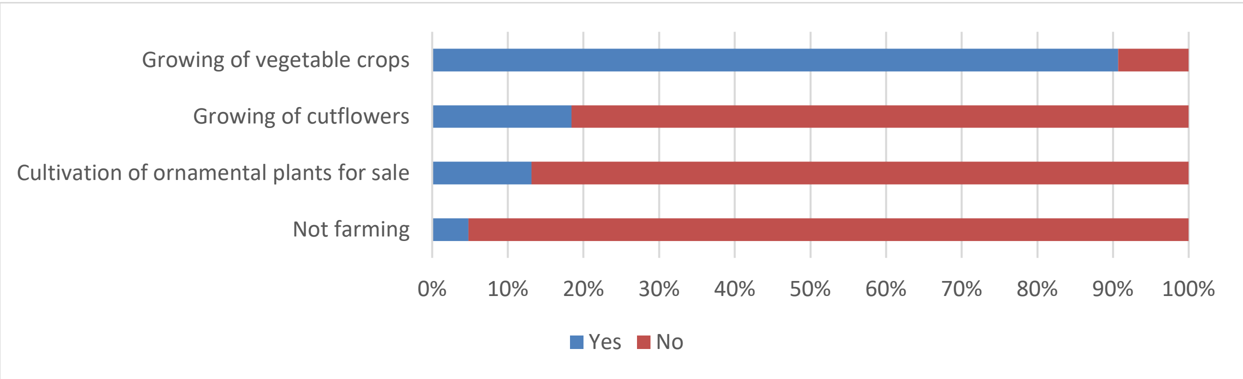
Table 2. Distribution of households interviewed by area of residence.

Area of Residence	Number of households	Number of household members
Sitio Macbas, Brgy Cattubo	46	79
Sitio Proper Paoay, Brgy Paoay	119	188
Sitio Toludan, Brgy Cattubo	74	129
Total	**239**	**396**

On average, the age of household heads is around 44 years old, which can reveal that they are relatively in their working prime and have already accumulated a few years of experience. Moreover, nearly 80 percent of these household heads completed their elementary education, while less than half (46.02%) have graduated from high school.

Based on the survey, a large majority of households in these areas are engaged in farming activities with 90 percent of household heads serving as farmers or hired farm workers. These households have been familiar with farming for years, with around 76 percent having at least five years of experience. An overwhelming number of these households (9 out of 10) were cultivating vegetable crops in 2017 (see Figure 1). Although it was also observed that not all were able to diversify their crops, with only 21.7 percent having more than one crop.

Figure 1. Farming activities of the household, 2017.



Households have an average of four members, while a great majority (87.8%) of households were headed by men (see Table 3). The majority of households own or have an owner-like possession of their house and lot. In terms of assets, the most common assets owned by households are radios, basic phones, and smartphones, followed by water pumps, vehicles, and tractors. Despite living in a relatively remote area, it can be observed that only a few households have access to personal transportation. Meanwhile, the most common form of device used for communication is radio with 84.5 percent having at least one, followed by basic phone (75.7%) and smart phone (69.5%). Ownership of these assets shows the importance of communication in a context wherein mobility is highly constrained.

Table 3. Household characteristics of respondents.

Indicator	Number	%share
Household size, mean	3.94	
Sex of household head		
Female	29	12.13
Male	210	87.87
Household Tenure Status		
Own or owner-like possession of house and lot	174	72.80
Rent house/room including lot	3	1.26
Own house, rent lot	2	0.84
Own house, rent-free lot with consent of owner	11	4.60
Own house, rent-free lot without consent of owner	3	1.26
Rent-free house and lot with consent of owner	46	19.25
Asset Ownership		
Radio	202	84.52
Basic phone	181	75.73
Smart phone	166	69.46
Computer	16	6.69
Motor	37	15.48
Vehicle	76	31.80
Tractor	63	26.36
Water pump	93	38.91
Green house	30	12.55

In the case of disasters, experience, knowledge, and asset ownership among others, are significantly important factors in handling shocks and recovering from them. The Philippines, due to its geographic location, has been consistently ranked as one of the most at risk when it comes to extreme weather events. Table 4 shows the disasters or shocks that households have experienced in the years 2017 to 2019. Among these incidents the most common one is typhoon, followed by frost, hailstorm, pest infestation, earthquake, and landslides. Of the households that experienced these events, more have experienced difficulty from these disasters. For typhoons, approximately three out of four households have trouble and would need time to recover. This is especially difficult given that these events do not occur for a single time and would happen multiple times in a year.

Table 4. Disaster/shocks experienced by the household in 2017-2019.

Disaster/Shock	No. of HHs that experienced the event			%share of HHs that experienced the event
	Did not experienced difficulty	Experienced difficulty	Total	
Typhoon	55	173	228	95.40%
Frost	39	119	158	66.11%
Hailstorm/Damage	30	108	138	57.74%
Pest Infestation	23	21	44	18.41%
Earthquake	10	33	43	17.99%
Landslide	10	25	35	14.64%

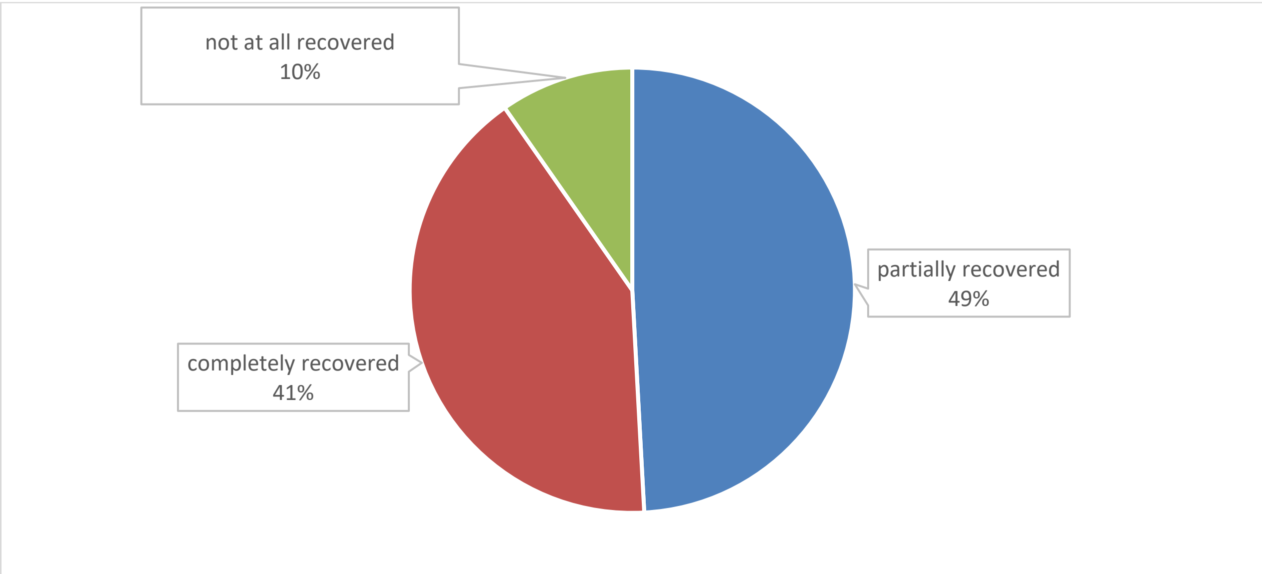
Increase In Food Prices	3	30	33	13.81%
Increase In Fuel Prices	3	24	27	11.30%
Financial Crisis	2	17	19	7.95%
Drought	0	11	11	4.60%
Flood	2	5	7	2.93%
Erosion	0	7	7	2.93%
Death Of Family Member	1	4	5	31.3%
Political Instability	0	3	3	18.8%

5.2. Recovery from disasters/shocks

In particular, the study is interested in looking at the underlying characteristics of households which may have helped them recover from the shocks and natural disasters mentioned in Table 4. In Figure 2, less than half of all households that experienced difficulty due to a disaster were able to completely recover after two years. In general, recovery takes a longer time for some households, given that only 49 percent were partially recovered after two years while one out of ten households made little to no progress during that time.

However, a notable limitation of the survey questionnaire used is the absence of a clear and comprehensive definition for the concept of recovery. Additionally, the questionnaire fails to specify the types of disasters from which the respondents have recovered. This lack of clarity obscures the context and scope of their recovery experiences, rendering the results less informative and difficult to generalize.

Figure 2. Recovery status of households that experienced a disaster after two years.



The distribution of households based on their recovery status and demographic profile is presented in Table 5 and Figures 3 and 4. Among those who have experienced typhoons, it is noteworthy that nine out of ten households have achieved at least partial recovery. This pattern also holds true for households that have encountered frost and hailstorms.

Interestingly, households with older heads are found to be less likely to achieve complete recovery. However, the relationship between recovery status and educational attainment does not appear to exhibit a clear pattern or correlation.

Table 5. Disaster/shocks experienced by the household in the past two years by recovery status.

Disaster/Shock	No. of HHs that experienced difficulty			%share of HHs that experienced difficulty
	Completely recovered	Partially recovered	Not at all recovered	
Typhoon	70	86	17	75.88%
Frost	58	52	9	75.32%
Hailstorm/Damage	46	53	9	78.26%
Pest Infestation	6	13	2	47.73%
Earthquake	3	2	4	76.74%
Landslide	15	9	1	71.43%
Increase In Food Prices	8	18	4	90.91%
Increase In Fuel Prices	7	14	3	88.89%
Financial Crisis	4	8	5	89.47%
Drought	6	5	0	100.00%
Flood	1	4	0	71.43%
Erosion	0	6	1	100.00%
Death Of Family Member	2	2	0	80.00%
Political Instability	2	1	0	100.00%

Figure 3. Age of household head by recovery status.

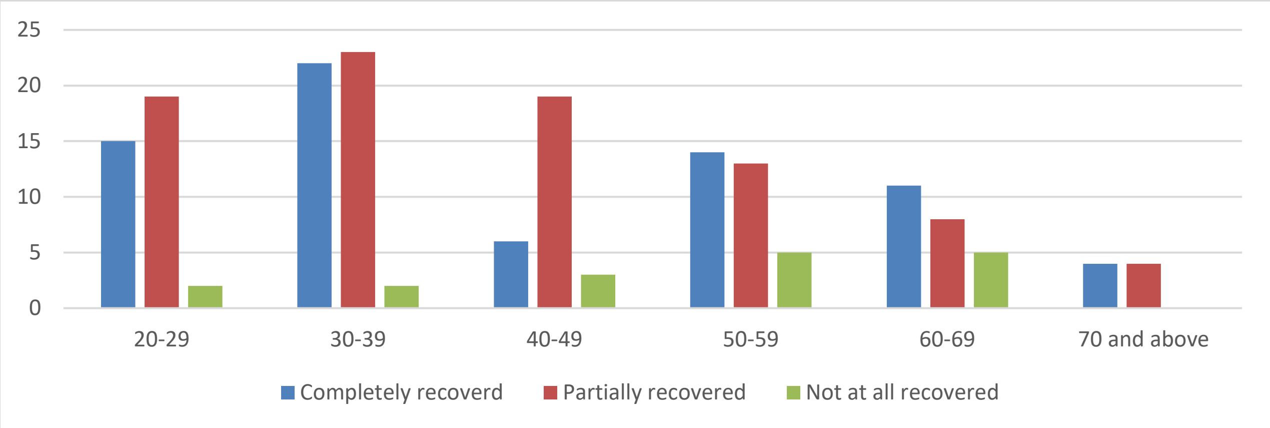
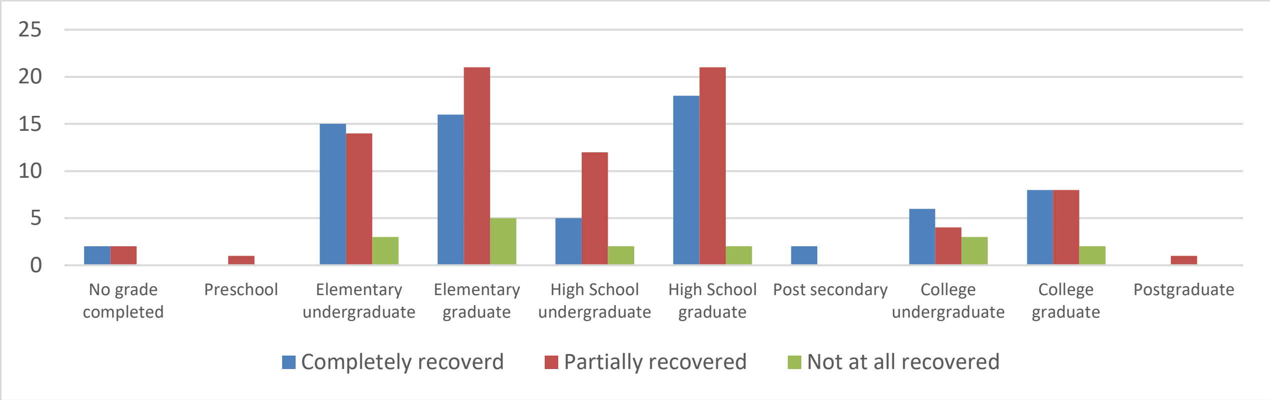


Figure 4. Highest educational attainment of the household head by recovery status.



In terms of the crops grown, Figure 5 shows that all growers of cut flowers have either partially or completely recovered. Conversely, among households not engaged in farming, there is a higher proportion of those who have failed to recover at all. Furthermore, it is worth noting that households with more years of farming experience have a higher share among those who were unable to recover (see Figure 6). However, it is important to acknowledge that the relationship between years of experience and recovery status is not entirely clear and may require further examination.

Figure 5. Farming activities of the household by recovery status.

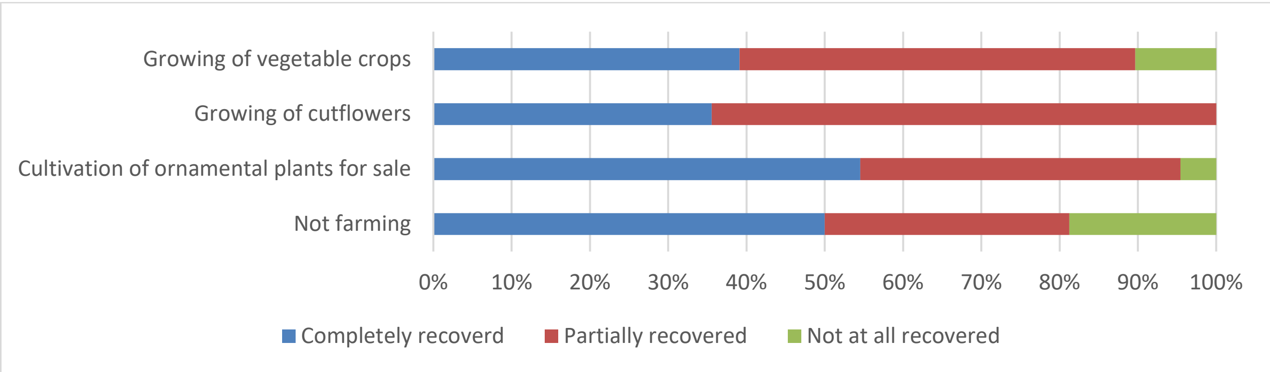
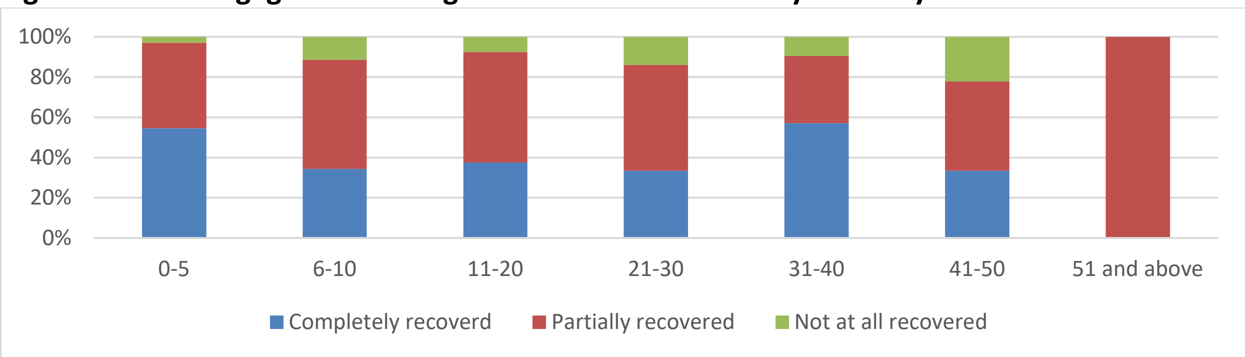


Figure 6. Years engaged in farming of the household head by recovery status.



5.3. Creation of a Resilience Index

Jayadas et al (2021) developed a resilience index for climate disasters at the household level in coastal farming communities in southern part of India using Principal components analysis (PCA). The use of PCA has been adapted in the study, however instead of using the dimensions proposed by Jayadas et al. (2021), the study incorporated the indicators mentioned in Schipper and Langston (2015) namely learning, flexibility, and options. Specific variables used per dimension can be seen in Table 6.

Table 6. Actual variables used per dimension.

Domain	Actual variables
Learning	HH head or spouse is at least high school graduate
	HH head or spouse has internet access
	HH is highly likely to adopt New technology
Options/Flexibility	HH has other income source
	HH has availed credit ever
	House floor area in sqm
	No. of vehicles owned by the HH
	No. of farm activities engaged by the HH

An asset ownership index containing information on ownership of items with direct impact on internet access and farming activity was also created, this contains namely basic phone smart phone, tractor, and water pump. In table 7, it can be observed that the above index is a highly significant determinant of the learning dimension. Moreover, network index (how highly connected households), years engaged in farming, and vehicle ownership are also important factors for the dimension.

Some aspects of these variables enable individuals to regularly communicate with others, for example vehicle ownership increases mobility which can make accessing physical information easier, this is similar with ownership of basic phones and smart phones (asset ownership index) and network index wherein individuals have direct access to their informants. While years engaged in farming focuses more on actual experience earned. In general, the above factors were able to explain the 78 percent of total variability.

Table 7. Determinants of learning dimension of resilience.

Variables	Model 1	Model 2	Model 3
Asset Ownership index	0.9542***	0.9447***	0.9480***
Network Index	0.0675***	0.0783***	0.0731***
Years engaged in farming	0.0081**	0.0078**	0.0046
HH availment of credit (ever)	-0.0880	-0.0597	0.0047
Total area of owned farm (hectare)	0.0004	0.0004	0.0003
No. of vehicles owned	0.2258***	0.2366***	0.2266***
Attendance in LGU seminars/events	-0.0808	-0.0580	-0.0250

Log of distance from usual venue of gathering	-0.0050	-0.0022	
Paoay dummy	-0.1232		
Observations	219	219	230
Adjusted R2	0.7852	0.7851	0.7814

Note: Standardized beta coefficients
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Author's computation, there may be possible errors for using generated variables in the estimation

Another index for options was also created, which contains information on household floor area, water pump and tractor ownership, as well as farm size owned. This is observed to be a significant factor for the options/flexibility dimension.

Table 8. Determinants of options/flexibility dimension of resilience.

Variables	Model 1	Model 2	Model 3
Years of schooling	0.0350	0.0256	0.0250
Asset Index for options	0.4167***	0.4739***	0.4182***
Paoay dummy	-0.3580*	-0.3586*	-0.3597*
Network Index	0.0033	0.0062	0.0027
Total area operated in the last cropping season (hectare)	-0.0058	0.0007	
Years engaged in farming	0.0102		
Observations	146	147	147
Adjusted R2	0.1213	0.1147	0.1119

Note: Standardized beta coefficients
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: Author's computation, there may be possible errors for using generated variables in the estimation

In terms of recovery status, the learning index and options/flexibility index are consistently significant for all three models, while total area operated is also significant at one percent. In terms of the option/flexibility index, this is more aligned with the literature wherein greater ownership of assets and diversified income sources can help households recover faster. Similarly, higher network index can also benefit households in their recovery from disasters.

Although all three models are considered significant, the result for the learning index is counterintuitive showing that higher learning scores have a probability of having lower recovery rates. This is also presented in the previous descriptive statistic (see Figure 4), wherein the bulk of those that have recovered are high school graduates, elementary graduates, and elementary undergraduates. This requires a more nuanced examination, given that the sample size for those with higher education is few.

Table 9. Ordered logit regression of HH recovery status.

Variables	Model 1	Model 2	Model 3
Learning index	-0.3368***	-0.3435***	-0.3655***
Option/Flexibility Index	0.3380**	0.2968*	0.3083*
Network Index	0.1217*	0.0946	0.1126
Total area operated in the last cropping season (hectare)	0.0022*	0.0024*	
Years engaged in farming	-0.02256		
Cut 1	-2.572	-2.118	-2.184
Cut 2	0.378	0.7919	0.686
Observations	126	126	126
Pseudo R2	0.0761	0.0664	0.0506

Note: Standardized beta coefficients

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author's computation, there may be possible errors for using generated variables in the estimation

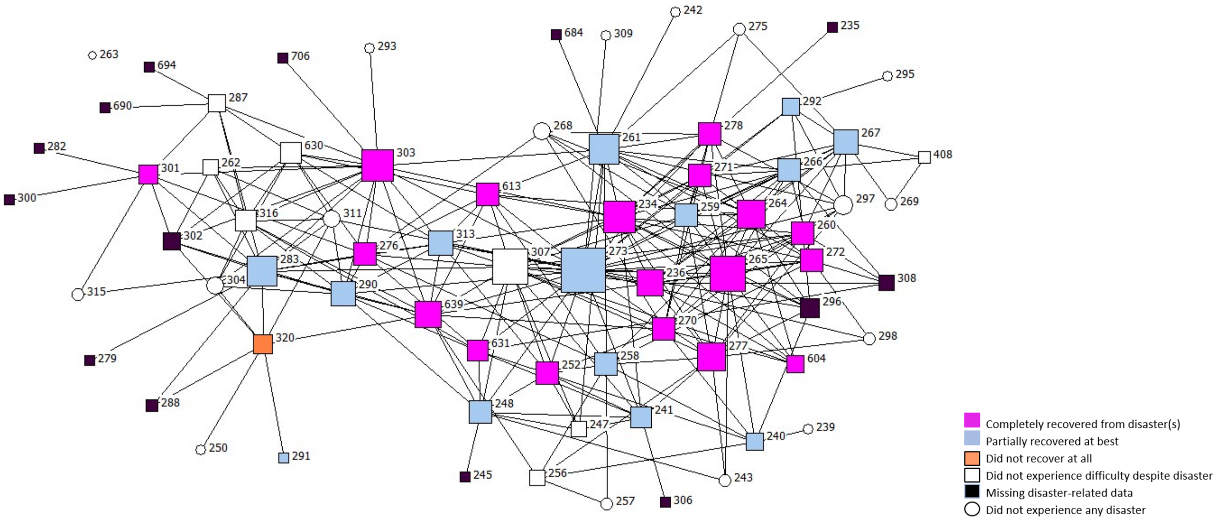
5.4. *Network Centrality and Resilience to Disasters*

The relationship between demonstrated resilience and network connectedness is explored by mapping their social network. In this analysis, it is expected that households that have fully recovered from disasters or shocks are likely to be strategically positioned within the networks, as they possess higher social capital. Being centrally located or at the core of the network signifies that these households have a greater number of connections or more strategic connections, thereby putting them at the advantage for resilience.

In the context of the social network, which encompasses kinship, friendship, and economic networks within the community, each node or element represents a household. The connections among households are depicted through dots, squares, or circles of various sizes. The size of a node reflects its level of connectedness, with larger nodes indicating higher scores in terms of connectivity. Degree centrality is a term used to describe the measure of connectedness for each household within the network. A high degree of centrality indicates that an individual or household has a significant number of connections within the network. In other words, they are well-connected and have established relationships with a large number of other nodes in the social network.

Figure 7 shows the social network of Sitio Macbas wherein the node sizes are proportional to the degree centrality. The nodes are color-coded according to the attributes of each household. Pink nodes represent households that have fully recovered from the disaster or disasters. Light blue nodes indicate households that have partially recovered. Orange nodes represent households that have not recovered at all. White nodes signify households that did not experience difficulty despite the disaster or shock. Additionally, black nodes represent missing disaster-related data, while circle nodes represent households that did not experience any disaster. If there exists a strong relationship between degree centrality and recovery, the size of the nodes will be larger.

Figure 7. Social network of Sitio Macbas (node size proportional to degree centrality).



Associating centrality with recovery or full recovery in the social network of Sitio Macbas proves challenging due to a substantial amount of missing data. This issue arose because, during the implementation of the survey in 2019, the interviewers relied on a pre-existing list of households. Unfortunately, this list did not include several new settlers in the area, even though they were identified as contacts or friends by those already included in the survey respondent list.

Furthermore, another factor contributing to the missing data is the potential lack of clarity regarding the boundaries of different sitios during the enumeration process. In such cases, it becomes difficult to accurately capture data for households within these unclear boundary areas.

Figure 8 shows the social network of the same Sitio Macbas, but the size of the nodes changes from degree centrality to betweenness centrality. Betweenness centrality is a distinct measure that focuses on a different aspect of importance within a network: it quantifies the degree to which a particular vertex lies on the shortest paths connecting other vertices. It helps identify individuals who act as crucial "bridge spanners" within the network, facilitating connections between different parts of the network (Hansen et al., 2020).

Once again, we do not observe a clear pattern. However, it is noticeable that households that have fully recovered, represented by the pink nodes, tend to occupy central positions within the network. Similarly, households that have only partially recovered also appear to be situated in relatively central positions.

Figure 8. Social network of Sitio Macbas (node size proportional to betweenness centrality).

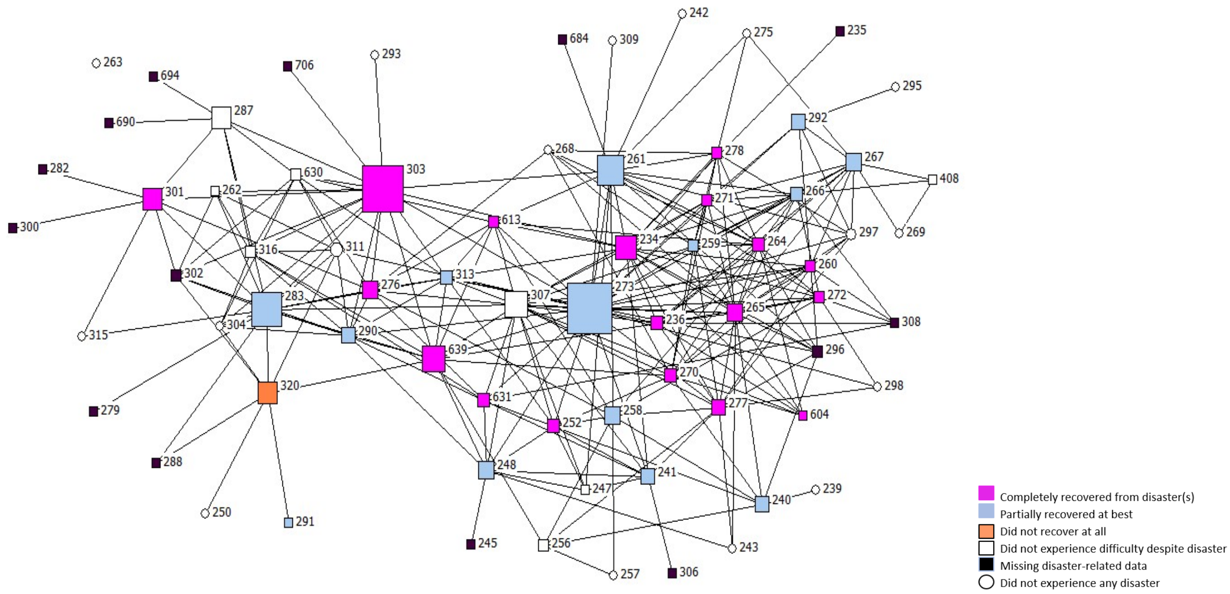
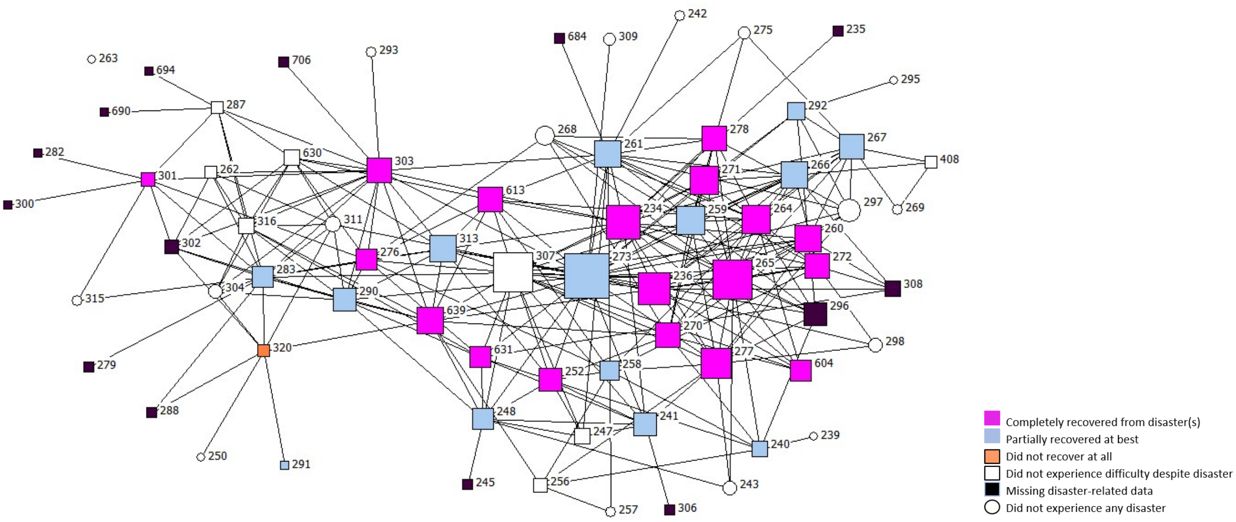


Figure 9 shows the social network of Sitio Macbas wherein the node size proportional to eigenvector centrality. Eigenvector centrality measures the importance of a node by taking into account the importance of its neighbors (Golbeck, 2013). It does not give importance to the number of connections, but who you are connected with. High eigenvector centrality score signifies that you are connected to a very potentially influential node in the system.

In the case of Sitio Macbas, the analysis similarly reveals a lack of conclusive evidence for such a relationship.

Figure 9. Social network of Sitio Macbas (node size proportional to eigenvector centrality).



Comparing the mean scores by group, we can see from Table 10 that in some instances, centrality scores of the *partially recovered* group are higher than those in the *completely recovered* group.

Table 10. Mean centrality scores by group – Sitio Macbas.

Group	Obs.	MEAN SCORES		
		Degree	Betweenness	Eigenvector
Completely recovered	18	11.8	88.5	0.489
Partially recovered	13	12.1	137.4	0.448
Not at all recovered	1	8	148	0.12
Did not experience disaster	18	2.7	4.7	0.102
Experienced any disaster but did not have difficulty	8	7.9	56.1	0.245

Figure 10 shows the social network of Sitio Proper Paoay wherein the node size proportional to degree centrality. Within the social network of Sitio Proper Paoay, it is worth noting that there are eight nodes represent households that *did not recover at all*. Those eight nodes do not occupy central positions within the social network. It is also observed that nodes of varying sizes, both the *completely recovered* group and *partially recovered* group, display larger node sizes within the network.

The betweenness centrality, as shown in Figure 11, also shows the same pattern.

Figure 10. Social network of Sitio Proper Paoay (node size proportional to degree centrality).

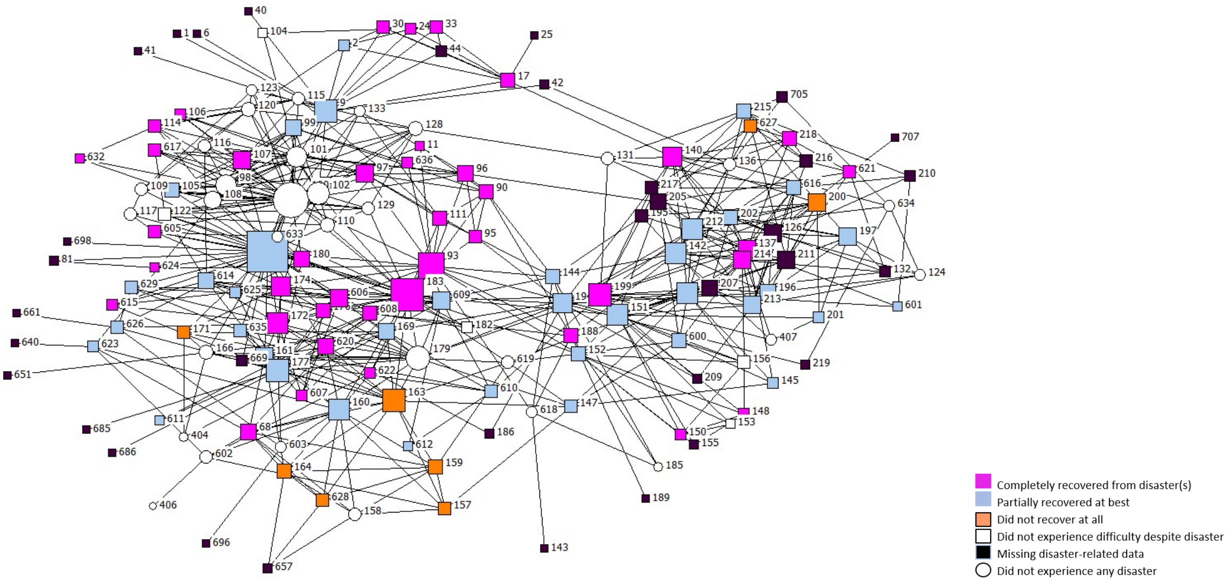


Figure 11. Social network of Sitio Proper Paoay (node size proportional to betweenness centrality).

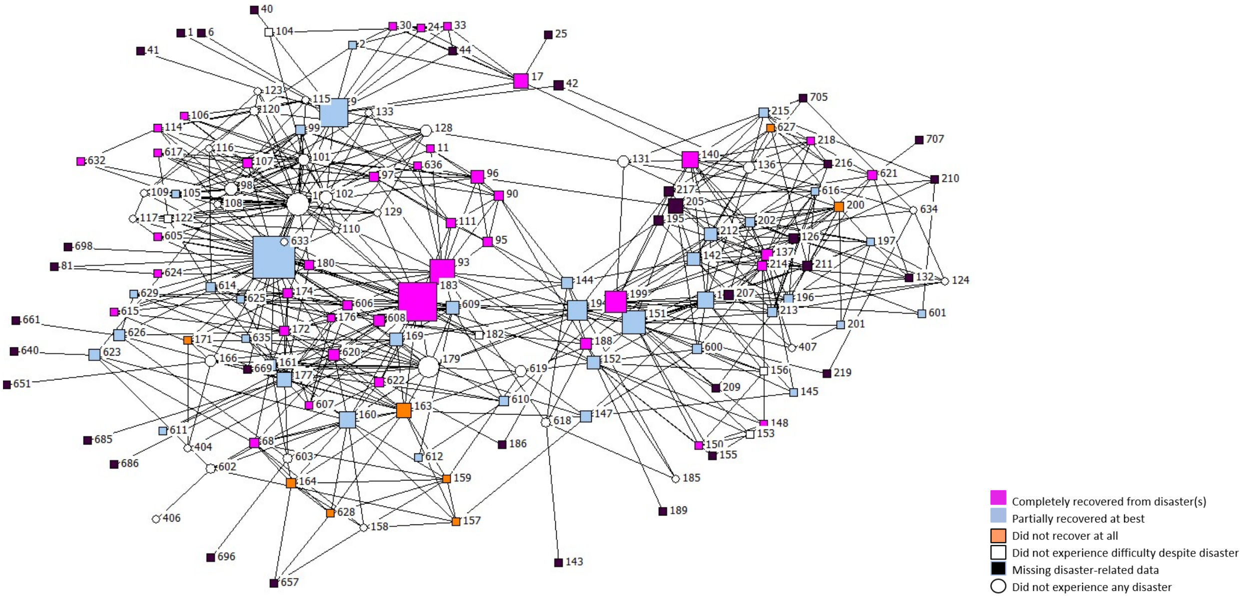
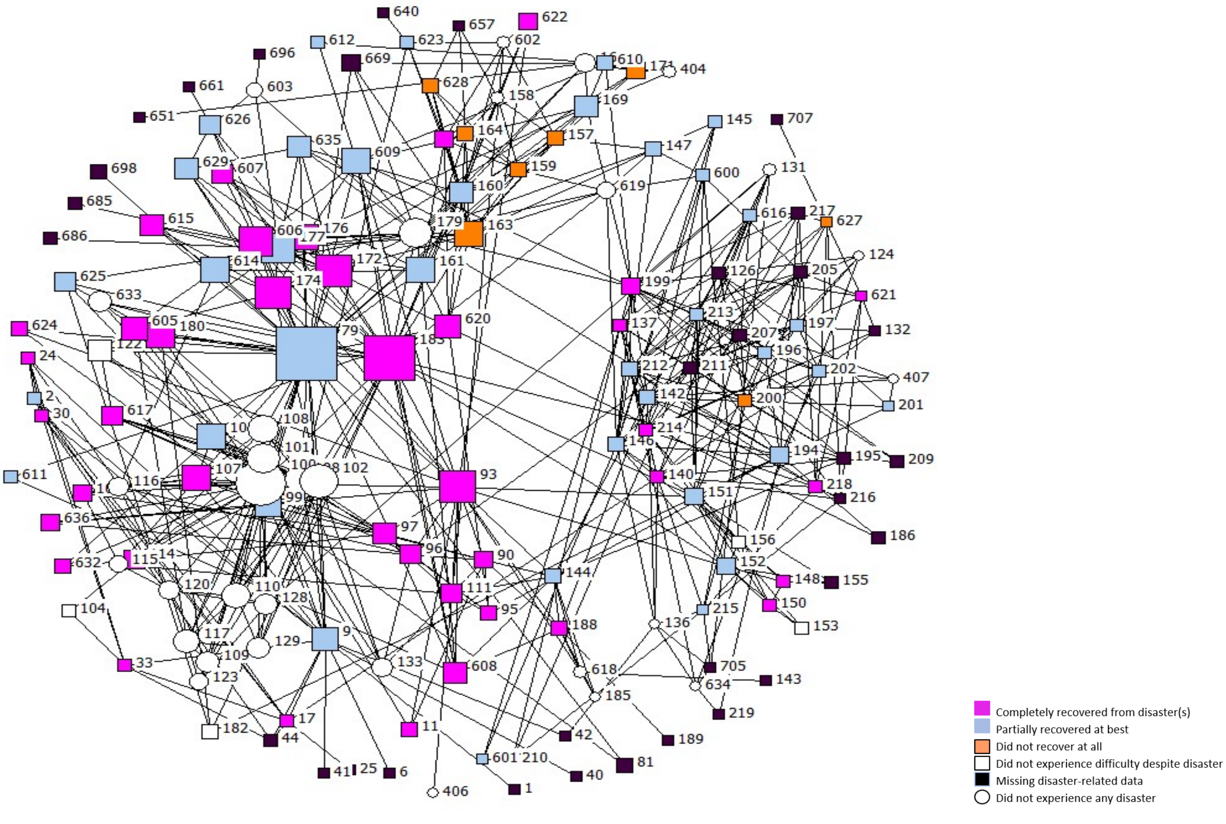


Figure 12 shows the social network of Sitio Proper Paoay wherein the node size proportional to eigenvector centrality. It can be easily seen who occupies the core of the network. The network is mostly occupied by households who have *completely recovered* and *partially recovered*. A distinction between the placement of households who have *completely recovered*, *partially recovered*, and *did not recover at all* is observed.

Figure 12. Social network of Sitio Proper Paoay (node size proportional to eigenvector centrality).



In terms of the mean centrality scores, it is observed that households who have *completely recovered* from disasters or shocks have a higher mean centrality score compared to households who *did not recover at all* (see Table 11).

Table 11. Mean centrality scores by group – Sitio Proper Paoay.

Group	Obs.	MEAN SCORES		
		Degree	Betweenness	Eigenvector
Completely recovered	40	8.87	205.5	0.201
Partially recovered	36	10.19	302.7	0.181
Not at all recovered	8	8.6	97.4	0.124
Did not experience disaster	16	.	.	.
Experienced any disaster but did not have difficulty	32	8.16	154.5	0.21

Note: * with missing data

The social network of Sitio Toludan has similar findings, as seen in Figures 13, 14, and 15, which show the social network of Sitio Toludan wherein the node size is proportional to degree centrality, betweenness centrality, and eigenvector centrality, respectively. Households who did not recover at all are not in the middle of the network. Most of the households who have completely recovered and partially recovered occupy the middle of the network.

Figure 13. Social network of Sitio Proper Paoay (node size proportional to degree centrality).

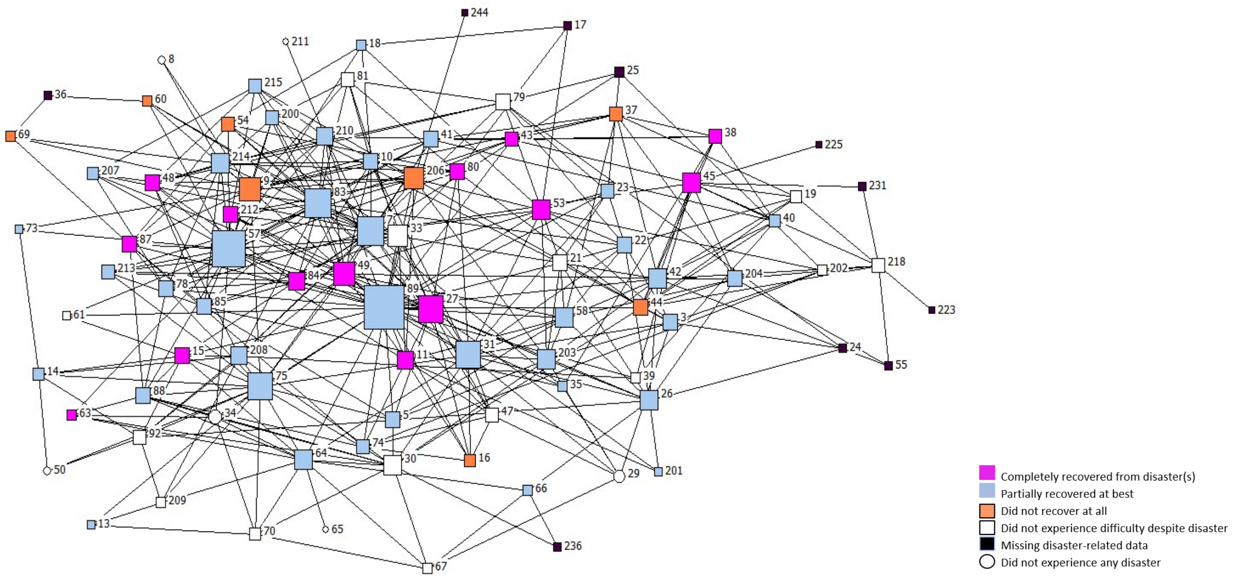


Figure 14. Social network of Sitio Proper Paoay (node size proportional to betweenness centrality).

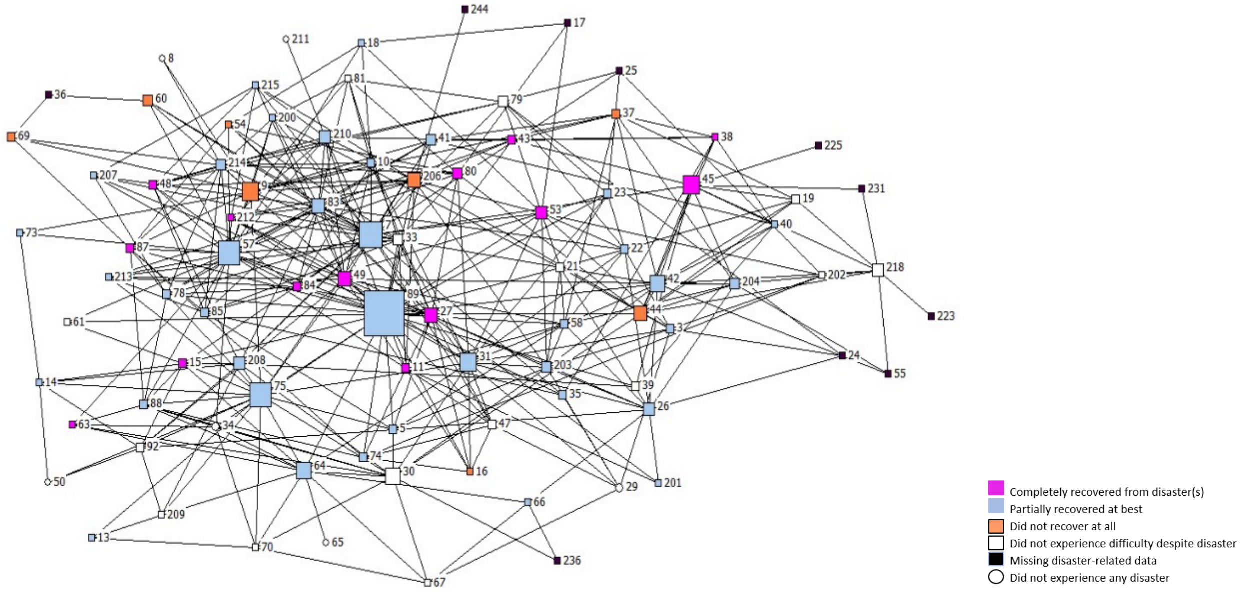


Figure 15. Social network of Sitio Proper Paoay (node size proportional to eigenvector centrality).

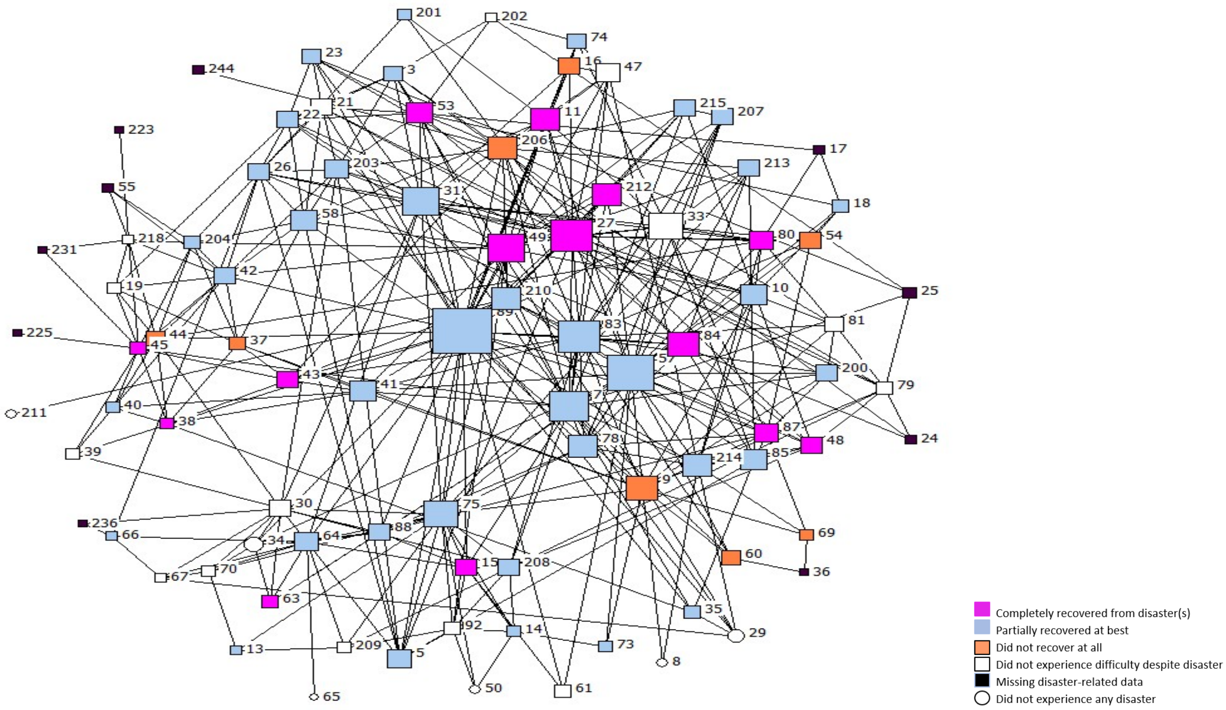


Table 12 below shows that the households who have *completely recovered* have a higher mean score than the households who have *not at all recovered* for eigenvector and degree centrality.

Table 12. Mean centrality scores by group – Sitio Toludan.

Group	OBS	MEAN SCORES		
		Degree	Betweenness	Eigenvector
Completely recovered	13	10.64	68.26	0.338
Partially recovered	37	10.78	99.7	0.312
Not at all recovered	8	8.75	84.85	0.259
Did not experience disaster*	9	3.33	8.15	0.089
Experienced any disaster but did not have difficulty	15	7.33	40.84	0.179

6. Summary and Insights

Upland farming areas like Atok, Benguet play a crucial role in attaining food security and improved agricultural productivity, and so we wanted to understand the characteristics of resilient farmers (and the least resilient). Resilience is multifaceted and it helps that we slice it into pieces that can be examined in a much deeper way. The framework by Schipper and Langston (2015) provided a way for this. We used already existing data that contained some information related to resilience and we conducted descriptive analysis, network analysis, and correlational analyses.

For the network analysis, we mapped those who have recovered completely from disasters within the network of social ties, and obtained objective scores of connectedness and see whether there was any relationship between recovering completely and connectedness. For the correlational analysis, we created variables of learning and options/flexibility dimensions via PCA. The PC scores were then used as dependent variables in regression analyses. We examined factors that are correlated with 1) having experienced difficulty, and 2) being able to recover from the disaster.

The network analysis failed to effectively establish the correlation between resilience (narrowly defined as having fully recovered from the disaster) and network centrality, but in the regression, we found significant outcome particularly in learning dimension of resilience. Notwithstanding data limitations, we found that the dimension "learning" is positively associated with wealth/assets, being strategically located within the social networks of the community, and having the means for movement or transportation (represented by vehicle ownership). Therefore, households who may need interventions in terms of the learning dimension are those in the bottom income groups, peripheral network actors and those without their own means of transport. In the 2021 paper, peripheral households are characterized as those who are living at the outskirts (far from common areas of social gathering), those without means of transport, and households who are recent migrants in the area. The dimension option is also significantly correlated with wealth which means that those with greater assets are also those with access to resources like credit, other income sources, diverse crops.

Limitations in the survey data constrained more nuanced analysis in that there was no clear information as to what the households were recovering from in the survey question about being able to completely recover from a disaster or shock. In the survey, this question pertained to any type of disaster. Since disasters or calamities tend to differ in terms of their effects, the study could not provide further details about how the households might have recovered. Future research will certainly benefit from expounding the type of shocks experienced so that the concept of recovery can be clarified. Furthermore, resilience analyses must examine factors beyond the control of households such as efforts implemented by local governments and physical and environmental attributes of the environment that households are situated in. It would also be important to control other factors that manifest household ability for self-regulation in times of calamities. The data issues can best be addressed if the survey instrument is designed for the specific purpose of examining resilience.

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