

Hub-and-spoke social networks among Indonesian cocoa farmers homogenize farming practices

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Abstract

Smallholder farms support the livelihoods of 2.5 billion people and their decisions on fertilizers use have profound sustainability implications. We investigated if and how social influence exerted through peer-to-peer information exchange affect the use of fertilizer among 2734 Indonesian cocoa farmers across 30 different villages. Results show that the structures of these village-based social networks strongly relate to farmers' use of fertilizer. In villages with highly centralized networks (i.e. where one or very few farmers holds disproportionately central position in the village network), a large majority of farmers report the same fertilizer use. By contrast, in less centralized networks, fertilizer use varies widely. The observed community-level distributions of fertilizer use are consistent with complex contagion mechanisms in which social influence is only exerted by opinion leaders that are much more socially connected than others. Our findings suggest significant policy implications for development programs targeting smallholder farming communities.

Main

Around 2.5 billion people work in smallholder farms providing 80% of the food consumed in much of the developing world [1]. Thus, to meet the United Nations Sustainable Development Goals of ending poverty and hunger by 2030, substantial productivity improvements are urgently needed in small-scale rural agriculture [2]. Indonesia is the fifth largest producer of cocoa with most of cocoa produced by smallholder farmers concentrated on the island of Sulawesi [3]. While the world's demand for cocoa has been growing, Indonesia cocoa production has declined by one third over the last ten years [4]. This decline has been linked to inefficient management practices and associated decline in soil fertility [3]. Many smallholder farmers attempt to offset insufficient productivity by increasing production area through deforestation – a major problem globally but particularly in Indonesia [5].

Smallholder farmers' choices of agricultural practices can have huge implication on their food security as well as their well-being [6]. Policy makers and development program managers routinely promote tested practices among smallholder farmers to foster food security, biodiversity, soil health, and water resource protection [7–9]. However, the vast numbers of smallholder farmers in remote communities make this endeavour very challenging. Further, these sources of information are not always reliable nor trusted by the farmers, and the experts' influence is often diminished when they move on to the next village [10, 11]. As a consequence, the most prevailing way for them to seek out alternative ways to tackle issues of sustainability might be to turn to their peers for advice [12, 13]. Hence, in these context the stakes of peer-to-peer social influence are high, but most studies of influence in social networks are done in different contexts, typically in the Global North [14, 15]. Therefore, a better and more context-relevant understanding of whether and how social influence in farmers' social networks affects their choices of practices can have implications for the livelihoods of billions [16]. Here we address this gap by investigating fertilizer use in 30 remote agrarian villages in the Indonesian island of Sulawesi encompassing 2774 farmers and their 3122 social ties with each other.

Opinion Leadership And Social Networks

Existing research suggests that much of what we do is influenced by our peers in social networks [14, 17]. However, influence within social networks is typically unevenly distributed and not all network relationships are consequential for our behaviour [18, 19]. One of the factors differentiating social influence is social status [20]. Peers of a higher status are more influential than others [21]. Peer status and influence can be defined as two sides of the same coin, i.e. being influential means that you have high status and vice versa [22]. Furthermore, the phenomenon where high status individuals have large and very disproportionate effects on decisions of others is at the core of studies of “opinion leadership” [23]. This phenomenon is routinely leveraged in the design of social interventions, education, training, marketing, as well as development programs that build on peer-to-peer information sharing and influence [24]. High status individuals are here targeted to promote innovation and entice others towards adopting desirable practices and behaviours who, in turn, are expected to influence their peers in their networks [25]. A caveat that needs to be considered is, however, that although high-status opinion leaders can influence crucial decisions of many others, this does not mean that they are the most informed individuals in their networks or engaged in the particular issues of interest to intervention organizers, nor that their advice and opinions are beneficial or relevant for everyone else [26–28].

Social status can be both a consequence and a driver of social network structure. Firstly, social status can be reflected and derived from prominent (i.e. central) positions in social networks [29, 30]. Secondly, social status can be self-reinforcing – actors in visibly central positions are typically perceived as having higher status, competence, and desired social capital and therefore are more attractive network partners [31]. This is called the “Mathew effect” or “preferential attachment” [32, 33]. These feedback mechanisms imply that opinion leadership is not only a phenomenon that can be isolated to the whereabouts of some specific individuals, rather opinion leadership shapes the ways all peers in the network are communicating with each other. The presence of strong opinion leaders drives network centralization – which is a macro-level property of a network where some individuals are significantly more central than others [34].

Although opinion leaders uphold these prominent positions, they nonetheless tend to be aware of, and act in line with, norms and expectations that prevail in their communities (in other words, opinion leaders are in general not unconstrained in what they can promote and enforce) [35]. This implies there is a risk that centralized network structures, in which the sources of influence are limited to a few prominent actors who in turn might tend to observe and follow the trends of the majority, could hamper members’ abilities to freely deliberate and address complicated problems [36]. Studies from laboratory experiments, student and research teams, and Western corporate teams have accordingly suggested that a dominance of a small number of highly influential individuals in a network stifles learning autonomy and decrease “the wisdom of crowds”, knowledge exploration, creativity, and experimentation of their collectives [37–39]. Whether these findings are valid outside the laboratories and online platforms, and in particular, in contexts such as smallholder farming in remote villages in low- and middle-income countries is, however, largely untested. Nonetheless, centralized influence exerted by opinion leaders, potentially stifling learning

and change, could have far-reaching consequences especially in contexts where informal social networks are the most readily-available channel for accessing information about essential practices to sustain one's living [40].

To examine the mechanisms of network centralization, opinion leadership, and social influence in agrarian communities, we analyse social networks and fertilizer use among smallholder cocoa farmers in 30 Indonesian villages by drawing on data originally collected by development organizations Koltiva/Swisscontact. We corroborate these analytical results with agent-based simulations replicating possible peer-to-peer social influence processes to test the hypothesis that farmers in highly centralized (so called hub-and-spoke) social networks characterised by the presence of high-status opinion leaders are more likely to be locked in the same agricultural practices across the entire network. The hypothesis is based on available evidence that smallholders' decisions to use a fertilizer partially depend on fertilizing practices of other farmers in their village and the structure of networks through which information and preferences influencing these choices are shared [11, 41]. Consistently with literature from other contexts, we hypothesise that centralized network structures will be associated with lower levels of farmers' exploration of, exposure to, and experimentation with locally less-prevalent (and potentially more productive) practices than what most other farmers apply. Further, we hypothesize that the practice being preferred by the most influential network member is also the most commonly applied practice.

Results And Discussion

Although the gathered data focuses only on farmers of the same produce in the same part of Indonesia, we find a large variation in the way agricultural information exchange networks are structured in the studied 30 villages, ranging from communities with widely distributed numbers of information-sharing links among their members and no single centre (Fig. 1, left) to an extreme case of a community in which everyone is connected to the most influential individual and no one else (Fig. 1, right). These differences in network structures can be quantified with the Freeman degree centralization metric [42]. The metric is based on the difference in the number of links of the node with most links in a network and the number of links of every other node, and varies from 0 to 1 (0-100% centralization). While the number of reported information links by a respondent varied between 1–4 (all respondents were prompted to provide at least one tie), the number of nominations an individual received by others as their agricultural information source goes up to 76. Such highly sought peers were present only highly centralized communities where the number of links to the vast majority of other community members was significantly lower (Fig. 1 for illustration, see Supplementary Information for descriptive statistics of all networks). Similarly to centralization, the prevalence of fertilizer use in the villages varies highly (between 0–78% of the village members were using fertilizers).

Ordinary least square regression results show that the prevalence of fertilizer use in a village is strongly associated with the structure of village-based social networks (The Pearson's correlation between $\log(\text{centralization})$ and fertilizer adoption ratio is -0.54 ($p = 0.002$). In highly centralized communities, where one farmer holds a very prominent position in the information-sharing network of the village, the

community as a whole to grow their produce with almost no fertilizer (Fig. 2). Specifically, very few people adopt fertilizers in such communities. Further, as a general trend the predominant community practice correlates with the practice of the most influential individual (the Pearson's correlation between a dummy variable indicating the most influential individuals' fertilizer adoption choice in each village, counted as 0.5 for villages with two most influential individuals with opposite practices, and the fertilizer adoption rate in the village is 0.69, $p < 0.001$).

This pattern is contrasted in less centralized networks where fertilizer adoption rates are more dispersed (there is a threshold at around 40% centralization as shown in Fig. 2). The difference between means of village-level fertilizer use rates below and above 40% centralization threshold (24% versus 4%, Fig. 3) is highly statistically significant (unpaired two-samples Wilcoxon test gave $p < 0.015$).

To control for other important network characteristics size, density, and clustering (measured as number of farmers, average number of ties per farmer, and the global clustering coefficient [43], we include these variables in a multivariate regression model. The number of farmers in a network and the average number of ties per farmer are uncorrelated with each other and the village-level centralization (Pearson correlation coefficients are < 0.37), but not the clustering coefficient and centralization (Pearson correlation coefficient is -0.85). Hence, to avoid multicollinearity, we did not include the clustering coefficient in the regression model (a different model where both centralization and the clustering coefficient were included is presented in the Supplementary Material, however the results from that model showed the clustering coefficient not to be significant while centralization remained significant).

Table 1
The relation between network structure and fertilizer adoption at the village level

Network structure	Coefficients (SE in parenthesis)
Centralization (Freeman degree, log)	-0.1800 (0.0507)**
Network size (number of nodes)	$0.8300 \cdot 10^{-4}$ ($3.160 \cdot 10^{-4}$)
Network density (mean degree)	0.0199 (0.0778)

Multivariate linear regression with the dependent variable indicating village-level fertilizer adoption rates (0–1). $N = 30$. **Significance at $p < 0.01$. To account for heteroscedasticity, the reported standard errors are based on the White-Huber sandwich estimator of variance (i.e. 'robust' standard error). Adjusted R-squared is 0.218.

In summary, all our findings are consistent with an asymmetric effect of network centralization on fertilizer adoption. Until a certain threshold (around 40% of maximum possible Freeman degree centralization), the effect of village network centralization on fertilizer usage is either weakly negative or on par with multifinality. Centralization levels above this threshold are unanimously associated with low fertilizer adoption.

Mechanisms other than influence exerted by opinion leaders that could potentially cause the observed results also need to be considered. In network terms, if influence coming through a relationship is dependent on other peers, it may be referred to as “complex contagion” (e.g., an individual may be influenced by its peers only if a certain proportion of its peers are in agreement)[44]. Complex social contagion is different from “simple contagion”, such as a viral spread (whether a virus transmission from one individual to another during close physical contact does not depend on other links these individuals may have to others) [45]. The differentiated influence that we elaborate here represent complex contagion, albeit from the sender’s point of view and not from the receiver’s point of view (an individual is only being influenced by a certain other if that other is much more socially connected than other individuals in the network).

To test alternatives to our social influence through opinion leader hypothesis mimicking a process of complex contagion, we first examine whether the observed patterns of fertilizer adoption across communities could be explained by a model of simple social contagion. If simple contagion was present, we would expect a relatively higher-probability of similar practice among any interconnected pair of farmers, possibly resulting in clusters (subgroups) of similar practices. We applied Autologistic Actor-Attribute models (ALAAM) to all villages with heterogeneous fertilizer use, but found no evidence of simple contagion in any of them (ALAAM cannot be applied in cases where fertilizer use is homogenous due to lack of variability, see Supplementary Materials).

Next, we tested a set of complex contagion mechanisms using agent-based simulation models (ABM; Supplementary Material). In addition to the status-based influence mechanism being at focus (influence is conditional on peers’ degree centrality, which is indeed an example of complex contagion), we test cognitive dissonance mechanism (the probability of being influenced is proportional to the number of peer adopters), threshold mechanism (following the practice of the majority of peers), echo-chamber mechanism (influence is much stronger if all peers use the same practice), and random peer influence mechanism (influence is exercised only by one randomly selected peer at any given time). The only mechanism that qualitatively reproduced the empirically observed patterns was the high-status model of opinion leaders. Specifically, the sudden homogenization of practice for networks above a critical level of centralization could be replicated only in ABMs in which the actors were influenced only by exceptionally highly central peers (2–4 standard deviations above the mean degree of the village). Even though we were experimenting with sliding parameters in all simulation models, the other tested mechanisms for complex social contagion did not consistently reproduce the situation of homogenous adoption outcomes in centralized networks and heterogeneous outcomes in decentralized networks.

The combination of the analytical results and the simulation results thus demonstrate that peer-to-peer social influence may be exerted only by exceptionally connected actors (who are present only in centralized communities). Thus, those who exert influence through their relationships are also those who have influence over many others, which leads to community-wide homogenous fertilizer usage in those networks where such individuals are present.

Two remaining and interrelated questions are how the high-status opinion leaders emerged, and why some village networks become so different from others? While we cannot use our dataset to answer such questions, we can draw some insights from qualitative interviews with research field assistants of the local partner organizations who have substantial experience of working across various Indonesian farming villages. The field assistants consider the existence of the exceptionally connected actors to be a legacy of previous external agricultural interventions that were delivered via a small number of selected local farmers (often being the leaders, or becoming the leaders, of externally-required local farmer groups for channelling interventions and subsidies), which as a side effect increased their prominence within their communities. Even though significant time has passed since then, the observed highly centralized networks (and their subsequent effects on fertilizer use) appear as imprinted into the social structures of these villages. This interpretation raises concerns regarding unintended long-term side effects of agricultural and environmental interventions and call for considerable caution before implementing any major programs that may alter social structures and processes in villages like the ones we studied here.

Conclusion

Smallholder farmers' choice of agricultural practices has consequences for livelihoods and food security of billions of people. Better understanding of the sources of influence on their practices is thus a matter of life and death for many. This study attempted to shed light on how social influence plays out in this context, and we found that in highly centralized (or "hub-and-spoke") social networks, farmers not only tend to apply the same practice, but that practice is typically to avoid using fertilizers.

The analytical findings combined with our simulations suggest that this is because farmers in centralized villages are disproportionately influenced by a small number of high-status opinion leaders. Our results are consistent with a complex contagion model in which measurable influence is exercised only through relationships to peers of degree centralities above certain thresholds.

However, the results are entirely different in villages with centralization levels below a certain threshold (around 40%). Fertilizer use varies widely across these decentralized villages, and neither the analyses nor the simulation models suggest any tendencies of peer-to-peer influence in such context. Peer-to-peer social influence thus appears to be exerted only by exceptionally connected high-status actors in centralized villages, which can explain why some villages appear as if collectively locked in sub-optimal practices, while villages without extremely highly connected high-status actors appear to be able to leverage the "wisdom of crowds" of diversity of opinions and transition away from the long-held status quo of not using fertilizers.

While a lot remains unanswered about the drivers of social influence in the examined networks because of the inherent limitations of cross-sectional observational research (and the many difficulties in gathering reliable data in these remote contexts), we can clearly state that we found no evidence of simple contagion. While models reflecting epidemiological processes have always been influential in social science (and arguably our general awareness has become even more saturated with epidemiological metaphors and diffusion curves since the Covid19 pandemic), our research in this context is in line with studies from Western industrialized settings demonstrating that simple contagion processes might not adequately describe the contagion processes that steer if and how social influence plays out across many different contexts. One practical policy implication arising from these findings is the need for more caution when implementing intervention policies, and in particular exerting extreme caution when elevating a small number of key program participants above others in ways that stimulate social network centralization in the targeted communities.

Methods

The data was collected by a non-governmental development organization Swisscontact and their partner Koltiva. Funded mainly by international governments and food production companies, the organizations have been surveying cocoa farmers in Sulawesi as a part of the support they channel to them through their sponsors in effort to understand the barriers to adoption of productive and sustainable farming practices. The average cultivated land area was 0.9ha and cocoa yields of these farmers were under 500kg/ha, which are levels considered well below potential and have been linked in Sulawesi to fertilizer misinformation and mismanagement [46]. While serious environmental damage can be done by uninformed application of fertilizers [47], replenishing nutrients, whether by organic or inorganic fertilizers, is always necessary in agricultural soil [48]. Appropriate use of fertilizers has profound implications on yield, soil health, water pollution, and greenhouse gas emissions [49]. Further characteristics of the sample are discussed in more detail in Supplementary Information.

In 2018, the survey included the question “Please mention people outside of this household, where you get advice, you can learn from, or who can provide information and knowledge related to farming practices, especially about cocoa”. The farmers have provided written consent that their data may be used for research. For the purpose of this study, the authors have obtained a completely anonymized subset of the secondary data with the approval of the human research ethics committee at the University of [anonymised]. The data required extensive cleaning, which is described in detail in the SI, and the implication of decisions made in the cleaning process did not substantially affect the main characteristics of the analysed subsample in relation to the acquired dataset. The cleaned data used in this paper include 30 villages varying in size between 31 and 365 farmers, with mean size 91 and median 75; 2353 respondents, who reported between 1 and 4 peers as their agricultural information sources, with mean 1.3 and median 1 (the total number of farmers in the village networks was 2774, meaning that some farmers in the networks were not interviewed, but still included in the networks since they were nominated by at least one respondent). Fertilizer adoption rates varied from 0–78% between villages. The

number of connections farmers have (i.e. network degree) varies from 1 to 55 (only accounting for links to farmers in the same village), with mean 2.29.

We tested our hypothesis by OLS regression, with and without logarithmic transformation (log-transformation was used to create more evenly distributed numerical values of the Freeman degree centralization metric), with and without accounting for heteroscedascity using robust standard error estimations, without and without all combinations of the following controls: network size, mean degree of centrality, and level of modularity (i.e. clustering – measured by the global clustering coefficient). In all cases, the relationship between high homogeneity of fertilizer use and high centralization was statistically significant. The relationship between centralization and prevalence of fertilizer adoption was, however, not smooth. By exploring the distribution of residuals, we can observe qualitatively different patterns of the outcome dispersion for networks above and below centralization levels of approximately 0.4. We compare and confirm the difference in terms of the fertilizer adoption outcomes for these two groups of networks by an unpaired two-samples Wilcoxon test.

To test whether the observed patterns of fertilizer use can be explained by simple contagion, we analyse the networks with heterogeneous fertilizer outcomes with Autologistic Actor Attribute Models (ALAAMs) [50]. ALAAM are used for cross-sectional network data to test, by Markov chain Monte Carlo maximum likelihood estimations, if certain network patterns can explain nodal attributes. Here ALAAM was used to test whether pairs of connected nodes are more likely to have the same value on the nodal binary attribute using fertilizer or not (more in SI).

To test alternative complex contagion mechanism, we ran simple agent-based models on two empirical networks (one centralized and one decentralized village network), in which the agents' probability of becoming influenced by their network peers is dependent on their other peers (i.e. complex contagion, i.e. exerted social influence is different from the algebraic sum of influences exerted through individual pairs of actors). If a certain complex contagion mechanism was able to reproduce networks with similar distributions of fertilize uses as in the highly centralized and decentralized empirical networks, we deemed is as a potentially relevant mechanism. These evaluations were not intended to single out what mechanisms are explaining the observed data, but rather to evaluate if a given mechanism could have possibly given rise to the observed results.

The presented qualitative insights come from 1-hour interviews and subsequent open-ended discussions and email exchanges with 5 members of the local partner organizations who conducted the data gathering in the field, and have decades of experience of working inside Indonesian cocoa communities and implementation of agricultural programs.

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Figures

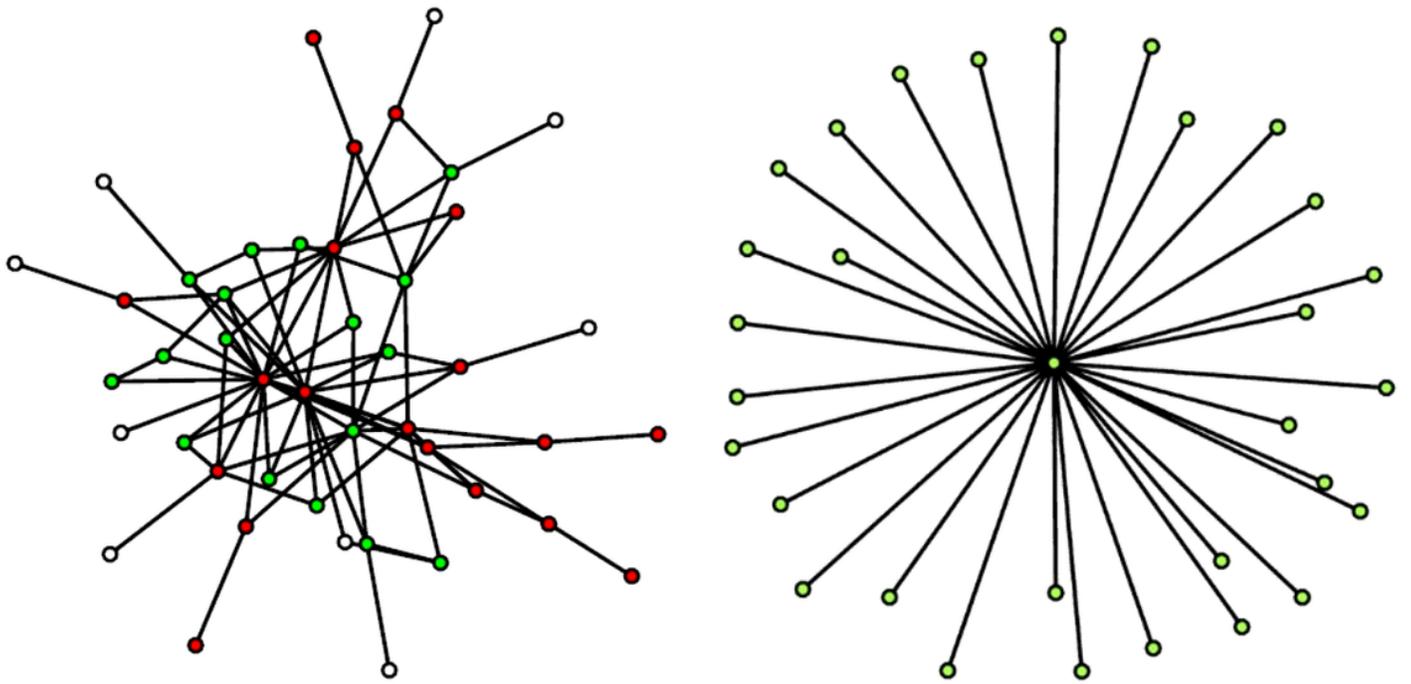


Figure 1

Examples of village information-sharing networks in the data sample. Left: a decentralized information-sharing network (Freeman degree centralization = 0.34). Right: completely centralized community information-sharing network (Freeman degree centralization = 1). Each circle represents a smallholder farmer; lines are reported information exchange links among them. Red circles indicate farmers who use fertilizer; green circles indicate farmers who do not use fertilizer (white is for farmers with incomplete data).

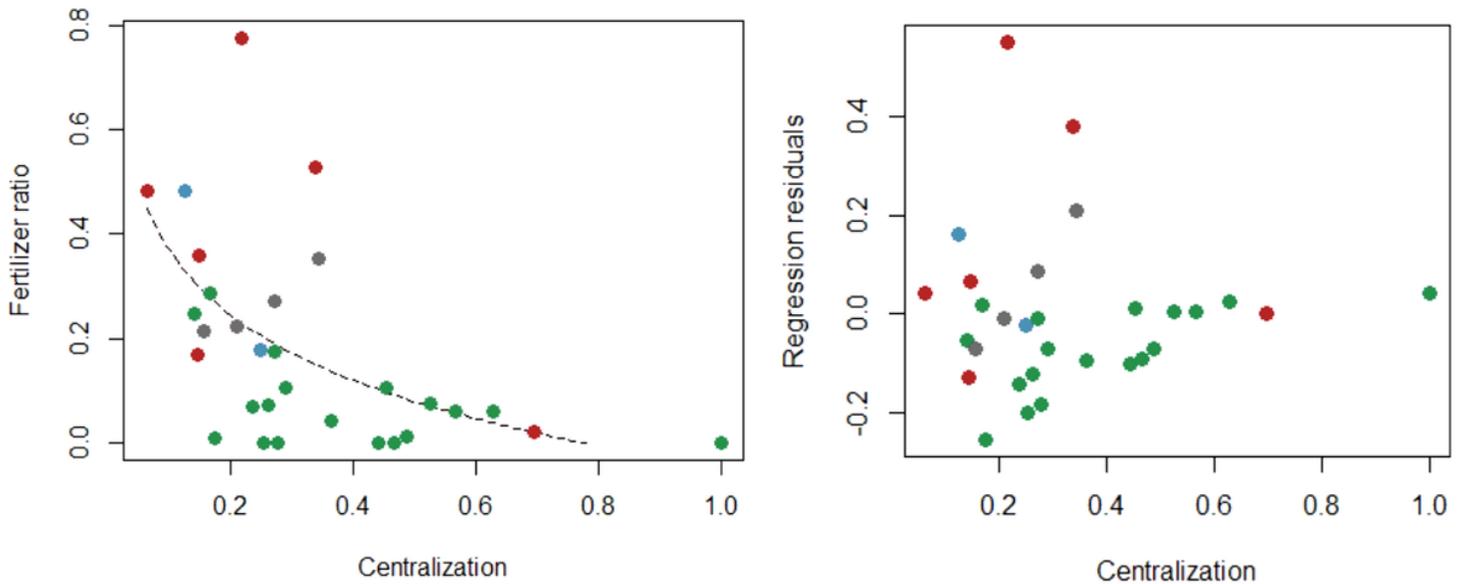


Figure 2

Network centralization and fertilizer adoption. The fitted curve to the left is based on a linear regression of fertilizer ratio based on $\log(\text{centralization})$. The grey area is 95% confidence interval of the fit. The colour of the dots depicts the practice of the individual with the largest number of links in the village: green means that the individual does not use a fertilizer, red means that they use fertilizers. Blue villages have two individuals with the same maximum number of links in the village, one of them uses fertilizers, one of them does not. Grey dots are villages with incomplete data. The diagram to the right shows the dispersion of the residuals of the fitted regression model. The dispersion declines rapidly for centralization levels above approximately 40%.

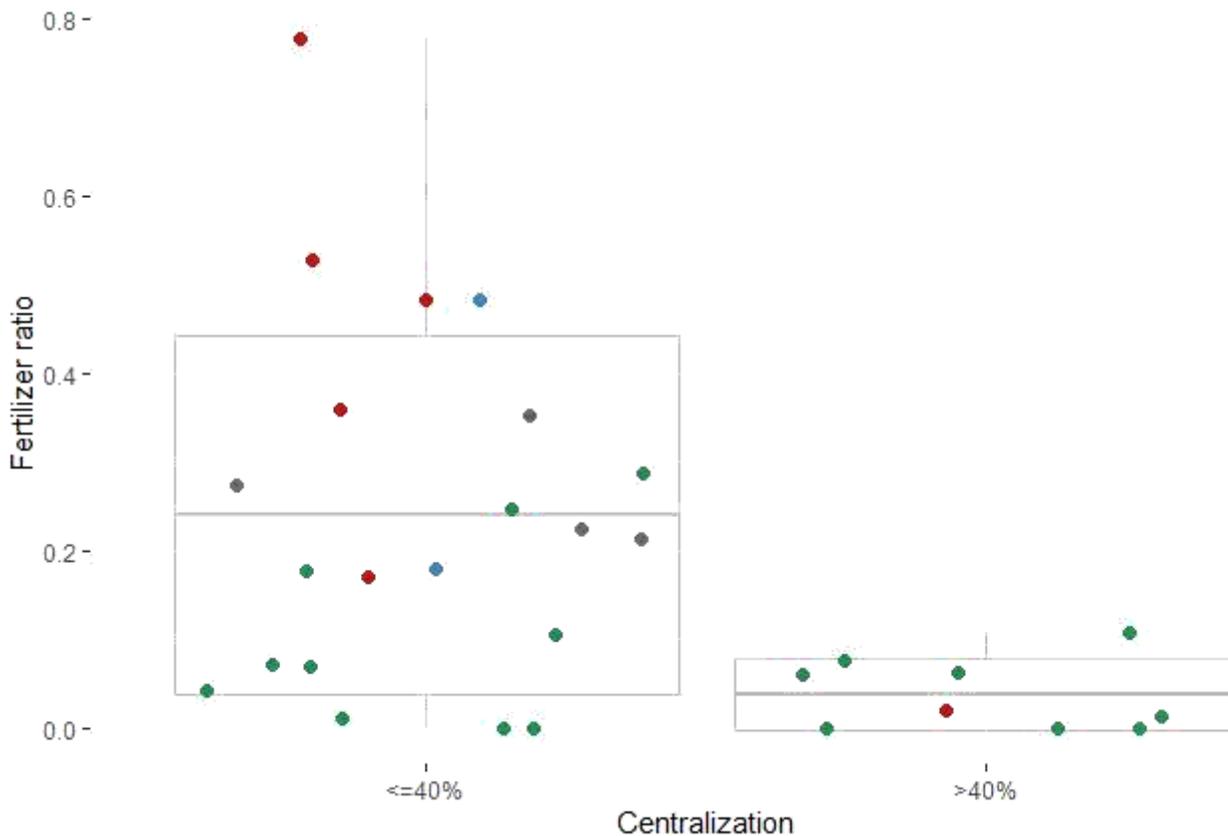


Figure 3

Fertilizer adoption ratios in villages below and above 40% Freeman degree centralization scores. Points depicting fertilizer ratios for villages in each category are horizontally jittered for visibility. Point colours are as in Fig. 2. The middle horizontal lines represent the means of the respective groups and the top and bottom lines delimit the range of one standard deviation from the means.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryInformation20210306.docx](#)