World Development 117 (2019) 112–126

Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

A comparative analysis of governance and leadership in agricultural development policy networks

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ARTICLE INFO

Article history:
Accepted 28 December 2018
Available online 21 January 2019

Keywords:
Agricultural development
Policy networks
Climate change
Food security
Smallholders
Global comparative data

ABSTRACT

Agricultural development initiatives feature many public and private organizations working together across sectors and scales to pursue the goals of food security and climate resilience. Policy networks are considered a crucial ingredient for the learning and cooperation needed to effectively implement agricultural development projects and increase community resiliency, yet very little comparative empirical data has been collected to assess where and how these networks operate. We contribute to filling this gap by characterizing the governance and leadership patterns within *agricultural development policy networks* that connect organizations working on climate resilience and food security activities in 14 smallholder farming communities across 11 countries in East Africa, West Africa and South Asia. We integrate theories of network governance and leadership in international development settings with social network analysis methods to analyze network structures and understand the roles of various actors working collaboratively toward agricultural development goals. We present two critical findings that advance our theoretical understanding of network governance and have implications for agricultural development policy globally. First, we find evidence for three distinct network types: *shared* and *brokered* networks, as predicted by the network governance literature, as well as a class of *fragmented* networks that exhibit extremely low levels of coordination at their core. Additionally, we find that while the presence of international development organizations is associated with greater overall network coordination, it is local and regional organizations that fill central network leadership positions most frequently. These findings suggest that resources may be an important factor in overcoming the cost of coordination, but social capital among local actors may be more important for developing network leadership.

1. Introduction

This paper comparatively analyzes the structure of *agricultural policy development networks* that connect organizations working on agricultural development, climate change and food security in fourteen smallholder farming communities across East Africa, West Africa and South Asia. The creation of policy networks is a key goal of local collaborative governance, which in the last two decades has emerged as a central development strategy for governmental and non-governmental programs alike (Ansell & Gash, 2008; Janssen et al., 2006; Provan & Kenis, 2008). The relationships embedded in policy networks span ecological, geographical and socio-political boundaries (Bodin & Crona, 2009), and potentially facilitate the cooperation and learning among international and domestic organizations that enhance social and ecological resiliency and adaptive capacity (Adger, 2003; Bodin, 2017; Brinkerhoff, 1996; Frankenberger, Constas, Nelson, and Starr, 2012; Smith & Frankenberger, 2018).

From an empirical standpoint, the study of networks has grown tremendously over the last decade in applied policy settings and even agricultural development contexts (Johny, Wichmann, & Swallow, 2017; Moore, Eng, & Daniel, 2003; Bandiera and Rasul, 2006; Stephenson, 2005; Udry & Conley, 2001). However, very few empirical studies compare whole networks across multiple communities (Provan, Fish, & Sydow, 2007), and thus comparative work on multiple networks working on similar challenges in different settings, are few and far between. By taking advantage of a unique global dataset from the CGIAR Research Program on

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https://doi.org/10.1016/j.worlddev.2018.12.015
0305-750X/

Climate Change, Agriculture and Food Security (CCAFS) that has tracked agricultural development activities in communities around the world, our work presents a rare comparative analysis of multiple agricultural development policy networks. CGIAR is a global research partnership that coordinates efforts between national and regional research institutes, civil society, academia, and development organizations focused on advancing agriculture and food security, while protecting natural resources and ecosystems. We analyze survey data collected from climate change and agricultural organizations working in 14 sites around the world to understand how actors coordinate to form different network structures in their communities. We assess and compare these networks on the basis of structural characteristics identified by the modes of network governance framework and international development literature. This paper is the first application of the partnership data from the full CCAFS organizational survey dataset and is the broadest geographical analysis of agricultural development policy networks to our knowledge.

Comparative analysis requires a useful theoretical framework for understanding the structure, composition, and function of policy networks. We adopt the modes of network governance framework developed by Provan and Kenis (Provan & Kenis, 2008), which has been extensively applied in public administration and public policy fields, most often in the context of health and environmental policy (Brinkerhoff & Brinkerhoff, 2011; Klerkx & Leeuwis, 2009; Lubell, Jasny, & Hastings, 2017; McGuire, 2006; Raab, Mannak, & Cambré, 2015).

The modes of network governance framework provides two important angles for studying agricultural development networks. First, it provides a typology of the types of network structures that are expected to emerge in different contexts. The framework predicts two primary network types that are differentiated by their density and centralization: highly centralized networks, or "*brokered*" networks, which can be led by a single or few organizations, and decentralized networks, or "*shared*" governance networks, with dense patterns of interaction between all actors and a larger number of highly central actors. By assessing the variance in network governance structures across communities, we can provide insight into the flavors of coordination that exist in agricultural development activities across developing contexts.

Second, the modes of network governance framework considers what types of actors are likely to serve in central leadership roles in policy networks, and thus allows us to provide insight into the debate in international development literature about appropriate roles for international versus domestic organizations in development initiatives. Central actors serve a number of functional roles in complex social-ecological settings, including screening for important information, amplifying the spread of that information, facilitating coordination of resources, and providing financial and technical capital to enable activities (Janssen et al., 2006; Perkin & Court, 2009). International non-governmental organizations (INGOs) have become a focus in development literature as critical actors that fill many of these roles, providing connections to other organizations, experience in implementing programs, flexible funding and risk-sharing capacity (Brass, 2012; Ingison, 2014; Perkin & Court, 2009).

In contrast, while local government organizations may under-compete in their ability to provide financial resources, they may have more legitimacy and social capital, given their embeddedness within their communities, from which they can motivate coordinated action from multiple actors. Furthermore, in certain contexts, there may be a state mandate for local government organizations to act as coordinator between all of the external actors within their region. The modes of network governance framework predicts different conditions will lead to network leadership from either organizations that are external to a community, or from "lead organizations" that come from within the community (Provan & Kenis, 2008). In this paper, we are able to examine the position of international (i.e. external) versus local (i.e. internal) organizations in different types of policy networks, and consider the potential implications of these network leaders on cooperation, learning, and political power in agricultural development activities.

To summarize, this paper focuses on the following key objectives: 1) assess the extent to which empirical agricultural development policy networks vary in structure in relation to the modes of network governance theoretical framework; 2) explore which types of organizational actors hold specific network leadership positions; and 3) understand the role INGOs play in the coordination of agricultural development policy networks. Our analysis here is limited to network structure as a first step to understanding how networks may influence the potential for upscaling and out-scaling climate smart agriculture practices and innovations, as well as household food security and agricultural success outcomes. While network theory provides some hypotheses about the link between structure and function, further research is needed to explicitly test those hypotheses.

2. Policy networks and actors

Collaborative governance arrangements comprised of multiple state and non-state actors have grown in their importance for addressing socio-environmental development challenges (Bodin, 2017; Brinkerhoff & Brinkerhoff, 2011; Clark, 1995; Janssen, Schoon, Ke, & Börner, 2006; Wieczorek, 2017). Understanding which actors are involved, what resources they bring into the collaborative network, and how they engage with one another are central to understanding the potential for networks to be effective in solving the problem at hand (Bodin, 2017; McQuaid, 2000; Perkin & Court, 2009). Specifically in contexts of food security and agricultural adaptation to climate change, collaborative governance networks have gained attention for their potential to leverage social capital, motivate coordination in crisis-response periods, and build community resilience (Davidson, 2016; Ramirez, Bernal, Clarke, & Hernandez, 2018). Additionally, social network analysis has become a popular tool for understanding how actors and institutions are connected, how information and resources are introduced and diffused across a network, and which actors broker important interactions.

Policy network researchers recognize the need for comparative studies of whole networks, pushing beyond individual case studies (Provan et al., 2007). To address this gap in the research, our paper adopts the modes of network governance framework (Provan & Kenis, 2008) to identify what types of network governance structures we expect to emerge in different communities and what types of actors we expect to play leadership roles in these networks. We then link the theoretical framework specifically to the international development literature by discussing the positions and roles of international versus domestic organizations in these networks.

2.1. Network governance theory

The modes of network governance framework differentiates networks that might be observed across communities in terms of centralized and decentralized structures, as well as what types of organizations might serve in leadership roles within these networks. *Brokered* networks describe highly centralized, hierarchical networks where a single actor sits between all, or nearly all, other actors, coordinating the majority of network exchanges and activities. The central actor brokering these exchanges can be external to the community, or a lead organization that is embedded within the community. *Shared* governance networks are decentralized, high density networks where the responsibility for network coordination is shared across many members (Provan & Kenis, 2008). Fig. 1 shows simplified depictions of brokered and shared networks.

An important benefit of Provan and Kenis' theoretical framework is the identification of key structural characteristics that should be measured as a basis for network comparison, each of which has been used extensively throughout network studies. This helps cut through the ongoing debate in the policy network literature as to which of the many potential network measures are most important for policy studies (Bodin, 2017; Bodin & Crona, 2009; Provan et al., 2007; Raab et al., 2015). Table 1 summarizes the structural features that we use in this paper to compare networks across sites, and their relevance to network function in development contexts. These variables include: total network size, density, degree centralization, fragmentation (measured as number of components), and average geodesic distance.

Based on this framework, we expect that it will be possible to classify the different observed networks in terms of brokered and shared network governance structures, with different types of organizations in central positions *(H1)*. These different modes of network governance will vary in their structural characteristics, with shared governance networks typically having more organizations, greater tie density, organized via decentralized structures that are less likely to break into fragmented subgroups. The standard hypothesis is that *shared* governance networks provide greater support for cooperation and learning, as long as there are high levels of trust and goal consensus among actors (Provan & Kenis, 2008). Shared governance networks have a higher density of relationships, where information can be exchanged among more pairs of organizations and trust-based, reciprocal relationships are more prevalent. Decentralized governance also emphasizes the importance of local knowledge and practical experience, and thus may be more likely to hone in on addressing the most pressing needs of developing communities (Ostrom, 1990). At the same time, shared governance networks feature a more even distribution of decision-making power, with no single organization steering the activities. In development contexts, shared governance networks are thus often referenced as a normative goal in the mind of development professionals. However, potential drawbacks of shared governance networks include high transaction costs of maintaining many collaborative relationships, losses in efficiency due to redundancy, and delayed or incremental decision-making when agreement among many actors is required for every advancement (Burt, 2004; Johanson & Mattsson, 1987; North, 1987; Provan & Kenis, 2008; Ramirez et al., 2018).

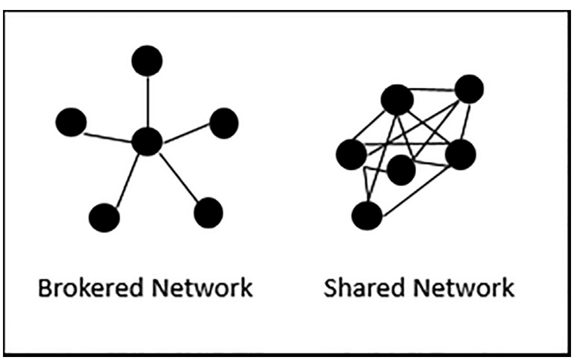


Fig. 1. Simplified example of brokered and shared networks for visual comparison.

The alternative to shared governance networks are more centralized, *brokered* networks, which can also be effective in particular contexts. In centralized networks, peripheral actors usually defer decision-making to one or a small core of lead organizations, that provide guidance on policy decisions and resources for implementation. In development contexts, these more peripheral actors may lack the capacity to effectively guide and implement development projects (Mitlin, Hickey, & Bebbington, 2007). Additionally, brokered networks may reduce the overall costs of decision-making, by relieving organizations of the necessity to establish and upkeep so many collaborative relationships, implementing top-down decision-making pathways, and enabling faster and more coordinated project implementation. This may be preferable in contexts where high levels of coordination are necessary or when economies of scale are beneficial (Ramirez et al., 2018); however, the potential benefits of brokered networks depend heavily on the capacity and intentions of the central network broker, or lead organization. Lead organizations with few resources, poor information, or ineffective leadership will compromise the effectiveness of the entire network. Lead organizations also have more political power as a network broker, which can be extremely problematic in development contexts if lead organizations are corrupt or have selfish policy preferences that are at odds with broader community goals (Gisselquist, 2012; Hoogesteger, 2016).

Table 1
Summary of key structural network characteristics for whole network comparative analyses.

Characteristic	Description	Relationship to governance, coordination, and development
Network Size	Total number of nodes (actors) in a network	Smaller networks tend to be easier to coordinate (Olson, 1965), but in development contexts size may indicate capacity or reach (Bebbington & Farrington, 1993)
Density	Proportion of ties (connections) present between nodes, relative to all possible ties	Density is positively correlated with trust and cooperation (Scholz, Berardo, & Kile, 2008), but may also lead to homogenization of capacity, reducing flexibility and adaptability required in development work (Bodin & Crona, 2009; Janssen et al., 2006)
Degree Centralization	Node degree (number of ties) distribution across all actors in the network	High centralization is positively correlated with coordination and collective action in some settings (Carlsson & Sandström, 2007), but also indicates power concentration on the central actor or "network broker" (Provan & Kenis, 2008); distributed "shared" governance has been promoted as a collaborative approach in developing settings (Ramirez et al., 2018)
Fragmentation (Components)	Grouping of nodes that are connected within, but disconnected to other groupings within the full network	Fragmentation reduces likelihood of coordination or cooperation across subgroups and reinforces in-group biases (Berardo & Ramiro, 2010; Fischer, 2014)
Average Geodesic Distance	Mean of the shortest path lengths among all connected node pairs in the network	Shorter distances between nodes increases the rate of diffusion of information and material resources, and enables learning (Bodin & Crona, 2009)

In this paper, we are primarily using the modes of network governance framework as a classification scheme to develop expectations about the types of networks we should observe. A stronger test of the Provan and Kenis framework requires predicting the type of network governance mode observed as a function of a set of preconditions, such as the amount of trust and agreement on issues (Lubell et al., 2017). Unfortunately, we do not have access to this type of data for our study sites; CGIAR did not set out to test this theoretical framework and a full test would require additional measurements. Furthermore, while the network governance framework does consider the effectiveness of different modes of network governance across contexts, here we are not directly measuring effectiveness. We argue it is an important starting point to observe the extent to which agricultural development policy networks conform to the types of network structures predicted by the theory.

2.2. Organization position

In addition to diagnosing structural differences, the network governance framework allows us to engage in the ongoing debate in international development literature and practice over the appropriateness of internal versus external leadership within development networks. The modes of network governance framework predicts different organizations will fill central leadership roles under differing circumstances. Lead organizations that are embedded within the community and provide their own services (i.e. internal), are predicted to fill central positions in networks with many actors with relatively low homophily in terms of goal consensus or domain similarity (i.e. actors are *less* similar to one another in goals, approaches and/or resources) and where greater social capital is needed to build cohesion across actors (McPherson, Smith-Lovin, & Cook, 2001). External organizations, which enter the community from the outside, are predicted to be located in central brokerage positions in complex circumstances, when the cost of coordination is high and access to resources is essential to effective coordination (Provan & Kenis, 2008).

These ideas from network governance theory can inform the messy debate in the international development literature about the appropriate role of different types of development organizations. Organizational networks in developing contexts became popularized in the 1990s when the World Bank recognized the importance of non-state actors and social capital as key policy tools that could provide public services and build local capacity, when state governments neglected these responsibilities (Banks, Hulme, & Edwards, 2015; Ramirez et al., 2018). At the heart of this debate is the distinction between importing capacity and resources of INGOs into under-resourced communities, versus relying on the local knowledge and potential legitimacy of domestic organizations (Brinkerhoff, 1996; Eade, 1997; Mitlin et al., 2007). One of few empirical studies of organizational networks operating in developing settings found that INGOs filled the central brokering positions in acute humanitarian response networks because of their ability to provide and distribute needed resources that were otherwise unavailable (Moore et al., 2003). In initiatives working to address long-run development challenges however, emphasis has been placed on capacity-building among local governments and organizations that already hold familiarity among their communities (Eade, 1997; Moore et al., 2003). This would lead to internal organizations filling central broker positions. For example, work by Bebbington argued that "islands of sustainability" can be achieved when local organizations take a leadership role in agricultural networks and empower rural smallholders by distributing technology and negotiating on their behalf with more powerful state and international actors for access to loans, financing and markets. Thus, the influence of local social capital can play a critical role in establishing legitimate leadership in local development projects (Bebbington, 1997). Of course, this discussion must also recognize critical viewpoints regarding competition among INGOs, displacement of local preferences by external preferences, and the possibility of rent-seeking and corruption among local organizations.

We use this theory and the limited base of empirical evidence to build our hypotheses as to which organizations will occupy the central positions in our agricultural development policy networks. The study sites selected for this survey effort were chosen based on a number of criteria, including the severe challenges their agricultural systems face from climate change and resource constraints, and their classification as "high potential sites" where ongoing CGIAR or national research infrastructure existed that could support data collection efforts and provide background climate and sociological information on the region (Förch, Sijmons, Mutie, Kiplimo, Cramer, Kristjanson, & Radeny, 2013) (see Methods for further discussion on site selection). These qualifications suggest that many of our study sites have both high need for network coordination to solve complex challenges of agriculture adaptations to climate change, and high likelihood of established contact with INGOs, given the history of the communities as development focus sites for the international community. Thus, we hypothesize that INGOs (i.e. external organizations) will be found most frequently occupying the central network positions *(H2)*.

2.3. Role of INGOs in network coordination

In addition to evaluating the organizational type of network leaders, understanding how the community of INGO actors influence network coordination is key to comparing these networks across sites and to advancing our understanding of the key functions of these networks to building resilience and enhancing food security, in the context of our data. Earlier development literature suggested INGOs play crucial roles in building collaborative governance in low income settings—providing resources, experience, connections, and risk-sharing (Clark, 1995; Lewis, 1998; McQuaid, 2000). The total number of INGOs active in sustainable development work however, has increased dramatically over the past two decades (Hoogesteger, 2016), bringing in a "new wave" of development that focuses on decentralized, participatory, local and democratic efforts, and "good governance" (Gisselquist, 2012). With this transition, development studies have only just begun to unpack the potential for INGOs to have a paradoxical effect, strengthening community capacity, building connections across sectors, and providing technical and logistical support, while simultaneously operating as gatekeepers that restrict local or national NGOs from accessing financial resources from the international community and national governments (Banks et al., 2015; Hoogesteger, 2016; Mitlin et al., 2007); this remains an area for further investigation and context-specific understandings.

From this literature we base our investigation and hypotheses on how the presence of INGOs will influence the coordination structures in the agricultural development policy networks we analyze. In sites where INGOs have been present and working for many years, we predict greater capacity building will have occurred, providing greater potential for cross-sectoral coordination and denser connections among local organizations and government actors. This, we hypothesize, will lead to greater likelihood of shared network governance structures. In contrast, in sites where INGOs are not present or have been less involved (i.e. fewer INGOs or fewer years of INGO presence), we predict less attention on capacity building, fewer established partnerships, and lower tie density in networks. This, we hypothesize will lead to greater likelihood of brokered network governance structures. In summary, we hypothesize that INGOs will be found more frequently in shared network sites than in brokered network sites (*H3*).

3. Materials and methods

This study was conducted to leverage the resources and data collection effort of the Climate Change, Agriculture and Food Security (CCAFS) Research Program. Various methods were applied throughout the full duration of this project, from the independent CCAFS Baseline Study data collection effort, to our analysis of the organizational networks present across three targeted regions: West Africa, East Africa and South Asia.

3.1. Data collection

The CCAFS research program selected core sites for each of their focus regions (East Africa, West Africa and South Asia) following two guiding principles. The first principle wasthe recognition of the multitude of actors (NGOs, government agencies, national agricultural research extension systems, farmer groups and private sector) who carry out much of the work around sustainable poverty reduction and improved food security, and their need for strong coordination and partnership. Second, CCAFS had a desire to work in sites where structures, institutions, projects and programs were already established, to leverage that infrastructure and not "start from scratch" (Förch et al., 2013).

A collaborative stakeholder group, including CGIAR partners and regional stakeholders, implemented these principles by participating in a site nomination and selection process, evaluating potential sites based on a specific set of criteria, that included: agricultural and climate challenges, socio-economic and demographic diversity, representativeness of the biophysical and agro-ecological gradients within their region, and opportunity for impact through research, governmental and non-governmental actors' work (Förch et al., 2013).

From 2010 to 2011, CCAFS research teams worked with local research partners in each of the following 14 study sites to collect data for the Baseline Study:East Africa: Makueni and Nyando, Kenya; Rakai and Hoima, Uganda; Lushoto, Tanzania; Borana, Ethiopia; West Africa: Lawra-Jirapa, Ghana; Segou, Mali; Kollo, Niger; Kaffrine, Senegal; South Asia: Bagerhat, Bangladesh; Karnal and Vaishali, India; Rupandehi, Nepal. We omit data from Yatenga-Tougou, Burkina Faso in this analysis due to large potential errors from inconsistent data collection. See sites on map in Fig. 2.

The CCAFS Baseline Study consisted of three data collection efforts that were replicated in each site: village resident focus groups, household surveys and organizational surveys. During the village focus groups, participants were asked to create an institutional landscape of their community by listing the most important organizations that were operating in their area and actively working on issues related to climate change, agriculture and food security, food crisis situations and natural resource management. CCAFS used these generated lists of organizations from each site as a basis for which organizations to enroll in the Organizational Baseline Survey (OBS). Locally-based research teams in each site reviewed these lists for accuracy and were given latitude to eliminate organizations they believed were not relevant or add any organizations they felt the focus groups had missed, based on their local/regional expertise. Teams then visited each organization in person to administer the OBS to a representative of that organization. Thus, the initial seed list of organizations for the OBS reflected both local knowledge and expert judgement as to which organizations were most important for local development projects.

Organizations surveyed included government agencies, NGOs, and private sector organizations, working at a variety of geographic levels (local, regional, national, international). On average across all

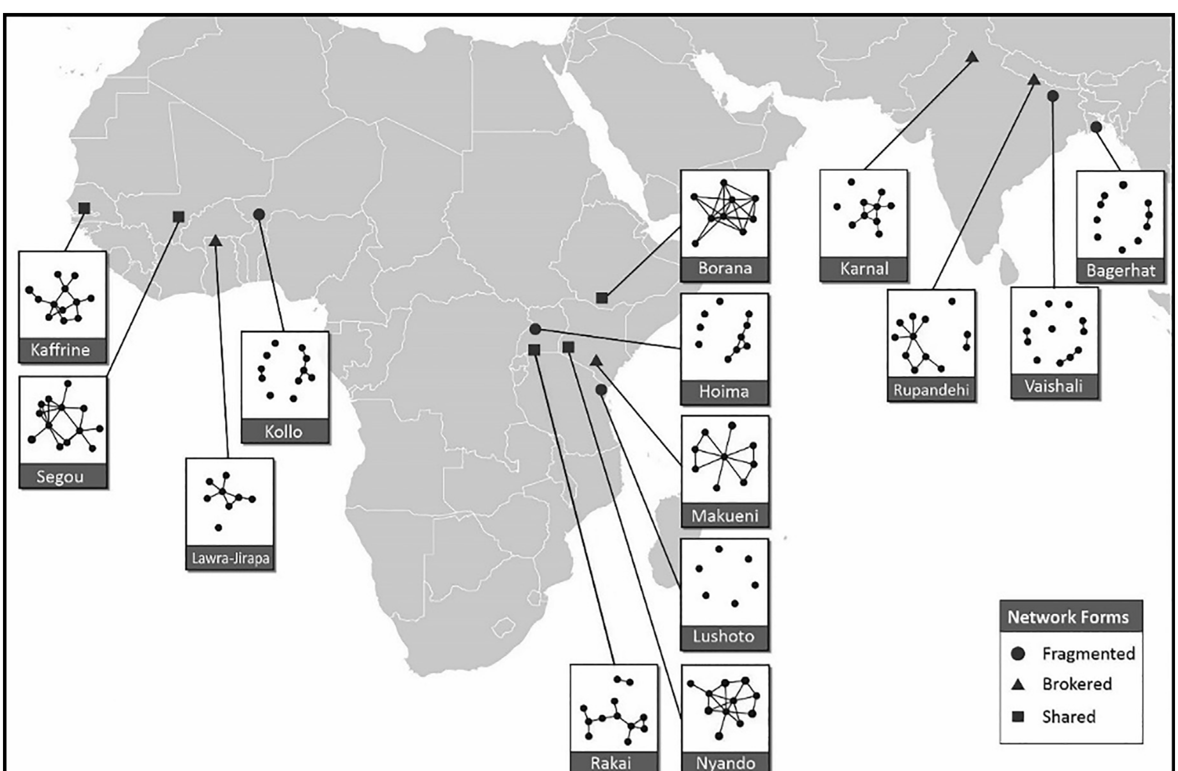


Fig. 2. Map of CCAFS sites with core organizational networks displayed. The shape of site markers distinguishes network governance types based on our classification of fragmented network sites (circle map marker), brokered network sites (triangle map marker), and shared network sites (square map marker).

sites, research teams contacted and successfully surveyed 68% of the village-nominated organizations and added an additional one to five organizations to the lists in each site, to ensure all key actors were included. Our network analysis utilizes data from a question on the OBS that asked organizations to name other organizations with whom they collaborated on various projects or work areas. The inter-organizational collaborations reported in these survey responses become the basis of our network data. We refer to the organizations that were surveyed in the OBS as our "core network organizations". We refer to the other organizations that were named as partners by core organizations while answering this survey question, but who were *not* surveyed themselves, as "periphery organizations". Because the periphery organizations were not themselves surveyed or asked for their collaborations with each other or with other organizations in the community, we focus only on the core organizations as a subset of the full organizational networks, for which we have the most complete relational data.

In total across 14 sites, CCAFS reached 145 *core* organizations with the OBS and 270 additional *periphery* organizations were named as collaborators, for a total of 415 organizations identified across all sites. We coded the collaborative relationship data to create adjacency matrices of binary variables indicating the presence or absence of a network tie (i.e. relationship) between every organizational dyad in each site. We used the organizational demographic questions from the OBS to create an attribute dataset for each core organization node, which included the organization type (i.e. government, NGO, private sector), the scale of the organization's work (i.e. local, national, international), the organization's work foci (i.e. what projects and issues they worked on), and the number of years working within the site. We then used the adjacency matrices to create a network graph for each site, where each organization surveyed or named is displayed as a node and partnerships between two organizations are displayed as a tie connecting the two nodes. We completed all statistical analysis and network graph visualization using R Statistical Software version 3.2.2 and the Statnet package (Hancock, Hunter, Butts, Goodreau, & Morris, 2003). See Appendix II for more detailed discussion on statistical analysis. All CCAFS survey tools, data collection protocols, and datasets are available open-access at https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/CCAFS-OBS-2012.

Our focus on the core network introduces important theoretical and methodological considerations. From the substantive standpoint, multiple network studies have focused their examinations on a central subgraph of the full network, or the "network infrastructure," arguing that the majority of the "networking" activity happens among these fewer, central nodes (Alexander, 2003; Robins & Alexander, 2004). This approach may be appropriate when resource or time constraints limit data collection to a subset of nodes in a network, or may serve to allow researchers to zoom in to actors that are believed to be central to the network activities, due to their positionality or functional role of holding more than one position. In our case, the core network was identified by local focus groups and expert knowledge, which supports the characterization of network infrastructure.

Nevertheless, ignoring the peripheral organizations for our analysis may potentially introduce bias if the unobserved relationships would dramatically change the network structures. Missing data of this kind is a common problem in network studies, and the subject of a growing literature (Smith, Moody, & Morgan, 2017; Borgatti, Carley, & Krackhardt, 2006; Smith & Moody, 2014; Smith et al., 2017). Some justification for this approach is provided by Smith et al. (2017), who find that most network measures are less sensitive to the missing data from peripheral nodes.

Regardless of these methodological points, it is important to examine the consequences of our analysis strategy for our specific empirical application. For our data, core nodes make up on average 35% of the nodes in the full network of each site. Yet despite comprising a large proportion of the overall nodes, the average degree of the excluded periphery nodes across all sites is 1.56, which is significantly lower than the average degree of the core nodes (4.20) across all sites. Furthermore, 94% of the periphery nodes across all sites have an in-degree below the average node degree of the core nodes within their own site, while 6% have in-degree that is greater than the average node degree of the core nodes within their own site. As we show in Appendix I, while analysis of the full networks results in less differentiation across sites in terms of density and average path length, the relative differences in terms of centralization and number of components remains largely the same.

Hence, we proceed with our analysis focused on the structure and dynamics of the core networks in each site, which includes the complete relational data between core nodes. Based on the village nomination process for the OBS and this comparison of degree centrality of the core and periphery actors, we feel confident that the core actors in each site *do* represent the majority of most centrally positioned actors working on agricultural development in their communities. However, we do acknowledge that our conclusions are constrained by data limitations, and Appendix I contains enough information for readers to critically evaluate our findings (Table 4 contains full and core graphs and network statistics for all sites, so side by side comparisons can be seen). More importantly, as we will discuss in the conclusion, the data limitations point to the importance of research design and network data collection in future studies.

3.2. Data analysis

Our analysis employed both quantitative and qualitative methods to better understand the variation in the core network structures and characteristics across sites. The small number of communities ($n = 14$ sites, which include 415 total core and periphery organizations) limits our capacity to conduct strong comparative statistical tests across sites. However, we do provide statistical tests where appropriate and we argue that it is reasonable to compare descriptive statistics across sites for general case study comparison (Onwuegbuzie, 2007), particularly given the lack of existing research in this area (Davidson, 2016). To account for potential concerns with the small sample size ($n = 14$), we run both parametric and non-parametric tests. Results are reported in the main text for the non-parametric tests; see Appendix II for results from equivalent parametric tests. The direction of all results are consistent across both parametric and non-parametric tests.

We calculated all network statistics based on the core network structures. To test *H1* on variation in network structure, we used the mean points of the following five descriptive network statistics from Table 1 to categorize each network into a network governance "mode": size, density, degree centralization, fragmentation (measured by components), and average geodesic distance. We evaluated the significance of differences in network statistic means using the Kruskal-Wallis test by ranks and *post-hoc* Dunn test. To test *H2* on organization position, we compared mean node degree of organizations working at the local/regional, national, and international scales and the identity of the actor with the highest degree centrality score in each site. Again, we evaluated significance of differences in mean node degrees using the Kruskal-Wallis test by ranks and *post-hoc* Dunn test. Finally, to test *H3* on the functional roles of INGOs within the network, we evaluated the linear relationship between the percentage of INGO actors out of total actors in each site and the network density, using a Spearman rank correlation. Additional details on statistical analysis included in Appendix II.

4. Results

We organize our discussion of the results according to the order of the hypotheses discussed above.

4.1. Modes of network governance

The agricultural development policy networks from each site are visualized and grouped by structural types in Fig. 3 and network statistics are summarized in Table 2. To test *H1* and categorize networks by structural type, we plotted density and centrality of each site and compared the means of various network statistics across groups, using the Kruskal-Wallis test by ranks with *post-hoc* Dunn tests (see Table 2). As expected, we found clear evidence for both shared (high density, low centrality) and brokered (low density, high centrality) network structures, in support of our hypothesis *H1*. Additionally, we found evidence for a third type of structure among our sites, which we call "fragmented" networks. Fragmented networks were an additional network structural type that we had not predicted to find, based on previous network governance literature. These networks were characterized by having extremely low density, low centrality, and a large number of isolated, unconnected components. Five sites had networks that could be classified as fragmented, with significantly more components than brokered ($p = 0.025$) or shared ($p = 0.001$) networks, significantly lower density than brokered ($p = 0.010$) or shared ($p = 0.003$) networks, significantly lower degree centralization than brokered ($p = 0.002$) or shared ($p = 0.035$) networks, and higher average geodesic distance than brokered ($p = 0.102$) or shared ($p = 0.008$) networks. Four sites had networks we classified as brokered structures and five sites exhibited shared governance structures. Brokered network sites had higher degree centralization ($p = 0.103$), higher average geodesic distance ($p = 0.142$), and a greater number of core components ($p = 0.142$) than shared network sites. All results using equivalent parametric means testing are reported in Appendix II Table 5.

4.2. Organization position

To assess what roles various types of organizations play in their networks and test *H2*, we identified the organization type of each site's most central (i.e. highest degree) node and compared mean node degrees of organizations working at local/regional, national, and international scales, using a Kruksal-Wallis test by ranks and *post-hoc* Dunn's tests. Contrary to our hypothesis *H2*, which predicted INGOs would most frequently operate the central position in a network, we found the most central nodes in all four brokered network sites were local (average degree = 2.00) or regional (average degree = 3.13) governments, indicating that internal lead-organization brokerage is more common. In three out of five shared sites, the most central nodes were local governments (average degree = 4.07) or local NGOs (average degree = 2.50), again indicating higher likelihood of leadership from an internal lead-organization (Table 3). Despite the local/regional scale actors filling the *most* central positions in brokered and shared governance networks, international scale actors were found to have slightly higher node degrees on average across all sites and significantly higher average node degrees than actors working at the national scale ($p = 0.018$). This can be explained by considering that international scale organizations were present in only one of the fragmented networks and fragmented network nodes had lower degrees on average, than nodes of other network types; thus for other organizational scales (i.e. local/regional/national) with more prevalence in fragmented network sites, the fragmented sites lowered the

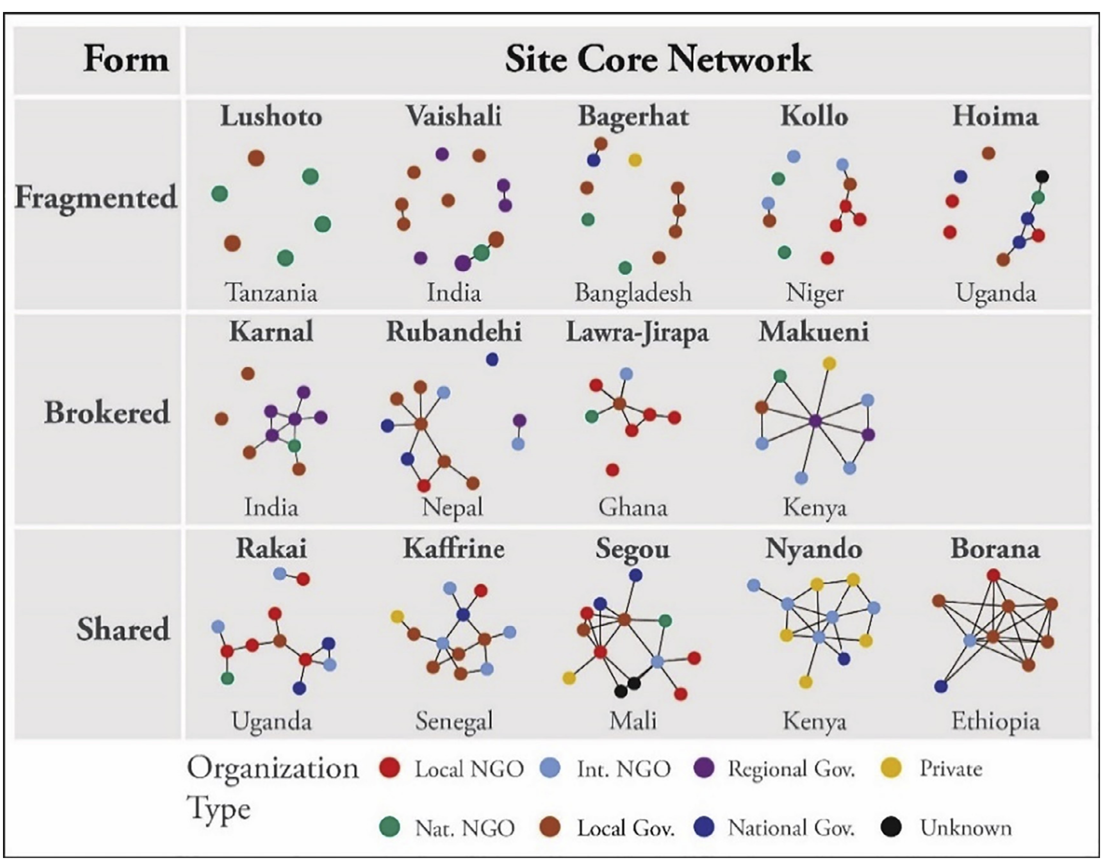


Fig. 3. Core network graphs for each site, grouped by network governance form. Nodes are colored by organizational type.

Table 2
Network statistic means across all sites and within each network governance form. We present network statistic means across all sites and within each network governance form (fragmented, brokered, shared); statistically significant differences in means between network types, based on non-parametric means testing using the Kruskal-Wallis Rank Sum Test, are denoted in the final row†.

Network Governance Form	Number of sites	Mean Network Size	Mean Number of Components	Mean Density	Mean Degree Centralization	Mean Geodesic Distance‡
All sites	14	10.4	3.36	0.20	0.37	4.43
Fragmented	5	9.8	6.40	0.07	0.17	6.91
Brokered	4	9.8	2.25	0.23	0.60	5.20
Shared	5	11.4	1.20	0.31	0.38	1.85
Krusksal-Wallis Rank Sum Test p-values	–	$p = 0.282$	$p = 0.005^{**}$	$p = 0.011^{*}$	$p = 0.011^{*}$	$p = 0.055$

average node degrees across all sites. In shared network sites, local/regional scale and international scale actors had comparable average node degrees, reflecting their greater connectedness overall and greater coordination between local/regional and international scale actors. In brokered network sites, international scale organizations had lower average node degrees than local/regional scale organizations, likely because these local/regional organizations were most frequently occupying the high-degree, most central positions. Results for mean node degree of all organizational types are reported in Appendix II Table 6.

4.3. Role of INGOs in network coordination

To evaluate the effect of INGOs on network connectivity, we used a Spearman's rank correlation, as a non-parametric equivalent to linear regression analysis, to test for correlations between network density and the percentage of actors in a network that are INGOs and the longevity of those INGOs in their sites, as predictor variables. We found a positive correlation between network density and the percentage of INGOs in a site (Spearman's rho = 0.58, $p = 0.031$), supporting our hypothesis *H3* that INGOs contribute to increased network connectivity. The average percentage of INGO actors in fragmented networks (5%) was lower than that in brokered (18%) or shared (25%) networks ($p = 0.092$). In fact, only one out of five fragmented network sites (Kollo, Niger) had any INGO presence at all, again providing support for the positive effect INGOs have on overall network connectivity. When looking at the effect of longevity of INGO presence in a site, we also found a positive correlation between overall network density and the average number of years an INGO was in a site (Spearman's rho = 0.659, $p = 0.010$) However, while we expected longer INGO presence in a site would lead to shared network structures and shorter INGO presence would lead to brokered structures, we found little difference in the average time INGOs have been present across brokered (20 years) and shared (17 years) sites. All results from linear regression analysis are reported in Appendix II Table 7; direction and significance of the results do not change between the use of parametric and non-parametric statistical tests.

Table 3
Mean node degree of organizations working at different scales§ We present mean node degrees for organizations working at the local & regional scale, the national scale, and the international scale, and compare their average node degrees across all sites and then within each network type.

Network type	Local/Regional	National	International
All sites	2.06	1.25	2.40
Fragmented	0.73	0.79	0.75
Brokered	2.23	1.40	1.43
Shared	3.23	1.89	3.25

§ Average node degree across all nodes and all networks = 1.90. Mean node degrees across organizational scales were compared using non-parametric Kruskal-Wallis test and significant differences are reported in text above.

5. Discussion

This paper is the first to use the CCAFS data to characterize and explore how agricultural development policy networks vary across region and place. Our analysis provides important insight on the structure and composition of inter-organizational collaboration in development contexts, where organizations aim to work together effectively and efficiently within local communities to build climate and agricultural resilience and food security. We draw two important findings that contribute to both the development of the modes of network governance framework and to empirical understandings of agricultural development policy networks.

5.1. Network governance types and coordination

We found distinctive centralized ("brokered) and decentralized ("shared") types of network structures present across our sites, confirming the usefulness of the modes of network governance framework for classifying variance in empirical network structures across communities. However, we also found an important third type of network, which we refer to as "fragmented" networks, which altogether show a lack of coordination across core actors. Within the context of the core networks, we interpret the lack of ties and isolated components of actors as an indication of structural isolation or independence of many of the organizational activities occurring among the core actors in these developing sites. Indeed, fragmented networks may be a network mode that is particularly important to devote attention toward in developing contexts where communities may lack ample resources and capacity, and these uncoordinated networks are most likely an indicator of inefficient development programs.

However, upon closer examination of both the core and full (i.e. core and periphery nodes included) networks in the sites classified as fragmented, we see that some of the core fragmentation may also reveal network measurement challenges and functional isolation. In a few sites (e.g. Lushoto, Tanzania and Bagerhat, Bangladesh), it appears that a few periphery nodes who were not surveyed in the OBS are in fact "popular" organizations named as collaborators of multiple other core nodes, and thus could potentially connect actors who otherwise appear isolated when just looking at the core network. However, the qualitative data in these sites' summary reports support our characterization of them as fragmented networks. For example, the Tanzania summary report reads: "*Another observation was a weak link between most organizations and the ward extension workers from Lushoto district council. This was confirmed by the fact that the majority of them [organization representatives] were not aware, apart from hearing here and there from few farmers, who are involved in the specific activity.*" Thus, we must question whether the "popular" but non-surveyed organizations have the functional capacity or motivation to meaningfully contribute to collaborative activities. Indeed, the fact that village focus groups and local experts missed these "popular" organizations in the first place suggests a lack of shared understanding about what organizations are centrally involved in the community. Hence, future research should not only invest more effort in surveying additional organizational nodes in the network, but should also devise ways to measure the contribution of each node to overall collaborative development programs.

From a theoretical perspective, our findings support expanding the modes of network governance theory to identify the contextual conditions that may predict fragmentation in organizational networks. While the importance of organizational networks have been widely recognized for their roles in supplementing state-provided services and development (Brass, 2012; Ingison, 2014; McQuaid, 2000; Perkin & Court, 2009), few studies compare sites where coordinated networks are prevalent, to those where coordination is lacking. Expanding the modes of network governance framework offers the opportunity to build a more accurate understanding of how organizations coordinate, or rather fail to coordinate, under certain contextual conditions.

To better understand these functional differences between fragmented, brokered and shared networks, it is critical for additional future research to facilitate more quantitative testing across network structures in more sites. To more strongly test the modes of network governance theory, we need more direct measures of the "contingencies" proposed by Provan and Kenis (2008), with measurements of network structure over as many communities and time periods as possible. These measurements of network structure need to be complemented by evaluations of the efficacy of organizations' activities in sites where organizational networks are well connected (i.e. shared or brokered networks), compared to sites where organizational networks are highly disconnected (i.e. fragmented networks). As with most policy studies, network and organizational analysis ultimately needs to be linked to measurements of outcomes, such as household food security and other indicators of community resilience, which is the next step in our research team's analysis. The CCAFS research program is advancing forward in this direction, with expansion into the regions of Latin America and Southeast Asia and planned follow up data collection efforts to return to these original Baseline Study sites. We look forward to working collaboratively with CCAFS to design the next phase of organizational network data collection, in order to facilitate these more robust and longitudinal analyses.

5.2. Leadership in agricultural development policy networks

Our results show that it is local and regional organizations (government and NGOs) that sit in central network positions most often, not INGOs, as we and much of the development literature predicted *(H2)*. This finding is important since the development literature has long depicted INGOs as critical to multi-actor coordination (Bebbington & Farrington, 1993; Lewis, 1998; Mitlin et al., 2007; Moore et al., 2003). Instead, our findings suggest that locally-based organizations assume a more prominent role in brokering various network actors and activities, than do INGOs in many places. In all brokered network sites for instance, local and regional government organizations occupied the central node positions, while INGOs were often found toward the periphery of the networks. This suggests that local and regional governments may be generally well known by local NGO and private sector actors, and additionally are likely to be recognized as necessary partners by any outside NGOs entering a community to begin a project.

This central positioning of local/regional government bodies may support theories of leadership based on trust and familiarity (Lubell, 2007) or may reflect local policy environments that require INGOs to work through local government authorities. Recent international development work on community resilience has similarly found that centrally oriented, well–connected, internal organizations can help to facilitate the development of the social capital that is thought to be correlated with development efficacy (Benyishay & William, 2018; Conley & Udry, 2001; Davidson, 2016; Ramirez et al., 2018). However, both researchers and practitioners should be attentive to domestic development organizations in countries with young or weak political institutions and economies which may be particularly vulnerable to the capacity and corruption issues that plague development projects. Thus, understanding the processes which lead local governments to occupy central network positions is another crucial direction forward in this research.

Nonetheless, INGOs do still clearly have a role to play in agricultural development networks. We find INGOs present in nearly every coordinated network (brokered and shared) and absent from all but one fragmented network, and the presence of INGOs is positively correlated with overall network connectivity. We also see that this connectivity is *not* derived from a pattern of homophily, that is of INGOs partnering with one another in a site. Instead, INGOs are partnering frequently with different local and regional organizations. This suggests support for the literature on INGOs differentiating and specializing from one another to serve unique niches in the communities within which they work (Cooley & Ron, 2002). It also suggests that INGOs are deeply engaged with local and regional actors in their activities. These local partnerships are critical to achieving intended outcomes, since INGOs interacting closely with local government entities have amplified the success of community innovation and growth projects in numerous documented cases (Deering, 2014; Provan et al., 2007; Stephenson, 2005). The influence of INGOs on coordination in these agricultural development policy networks is thus more complex than is widely suggested in current development literature.

5.3. Limitations of this work

We acknowledge that there are multiple empirical limitations to this work. Most directly, the relatively small sample (n = 14 sites) from which we analytically compare network structural types constrains our ability to understand all variation in structural characteristics and our ability to derive generalizable network structural trends. Additionally, we acknowledge that a multitude of other factors, outside of coordination and inter-organizational relationships, could be driving variation in network structure seen across the 11 countries from which our data derives. These countries vary significantly in political and economic structures, and we are not naïve to think those influences have no impact on how organizations coordinate, how "coordination" is perceived and interpreted by the local organizational representatives who were surveyed, or which types of organizations sit in central network positions. We tested for impacts of country level Gross Domestic Product and Human Development Index as predictors of network structures, and found no significant relationships, indicating that network structural variations were not simply a product of straightforward, traditional development metrics. Additionally, in our Methods section we detail at length the limitations of the network data given the nature of the core-periphery structures that result from the OBS data collection process. In this paper, we present the best network analysis we can, given the nature of the data available in this global dataset, and must trust that the locally-based research teams that conducted these surveys characterized coordination partnerships in the most context-appropriate way possible. While these limitations should be considered, we also highlight them as justification for a greater focus on network data in agricultural development, to facilitate greater understanding across more regions in the future.

6. Conclusions

Agricultural development policy networks connect public and private organizations operating at various scales and across a diverse range of activities that potentially contribute to the tall order of building climate resilience and food security. Theory suggests that rather than competing for attention and resources, the many involved organizational actors and smallholders should collaborate to sustain programs that are adaptable and resilient to the global environmental and social changes that impinge on local social-ecological processes. The operation of these organizational coordination networks may take on a variety of different functions—from sharing knowledge and resources, to expanding the reach of partners, to contributing complementary efforts—but empirically analyzing the structure of these networks is helpful in understanding if and how they support desired outcomes.

Our research begins to provide insight into how these networks vary in structure and which organizational actors play crucial leadership roles. We find three distinct types of network structures—*brokered, shared and fragmented*—that we predict have varying levels of impact and efficacy, depending on the local configuration of social-ecological variables. Further, we observe strong patterns of local organizations capitalizing on legitimacy to occupy central network positions, and INGOs providing capacity to build network relationships. This research makes important contributions to the literature analyzing policy networks and network governance in emerging economies, including identifying the "fragmented" type of network structure and demonstrating the propensity of local and regional organizations to fill central network leadership roles. Additionally, we hope this research contributes to practical advances in understanding how resources may be exchanged across an organizational landscape and how various actors assume roles of network leadership, so as to provide insight on how to leverage these networks to make practical advances.

Future studies should be expanded to explicitly collect full network data, including partnership data from "periphery" organizations. These organizations may in fact do more of the on-the-ground implementation work; thus, information on how they participate in collaborative relationships offers valuable information on how development initiatives are coordinated and implemented. This expanded data collection will allow the evaluation of the full partnership network structures and can facilitate comparison of full to core network structures. Additional research should expand the sample of agricultural development policy networks, measures contextual social-ecological variables, and link network-level characteristics to outcome data of various organizational activities. This offers opportunity to improve how we understand the importance of networks for reaching development goals and to suggest concrete pathways forward for organizations to effectively work with communities around the globe to overcome pressing agricultural challenges in an era of rapid environmental and societal change.

7. Data statement

Our study utilizes the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) Organizational Baseline Survey (OBS) dataset, from which we construct and analyze policy networks.

All CCAFS survey tools, data collection protocols, and datasets are available open-access at https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/CCAFS-OBS-2012.

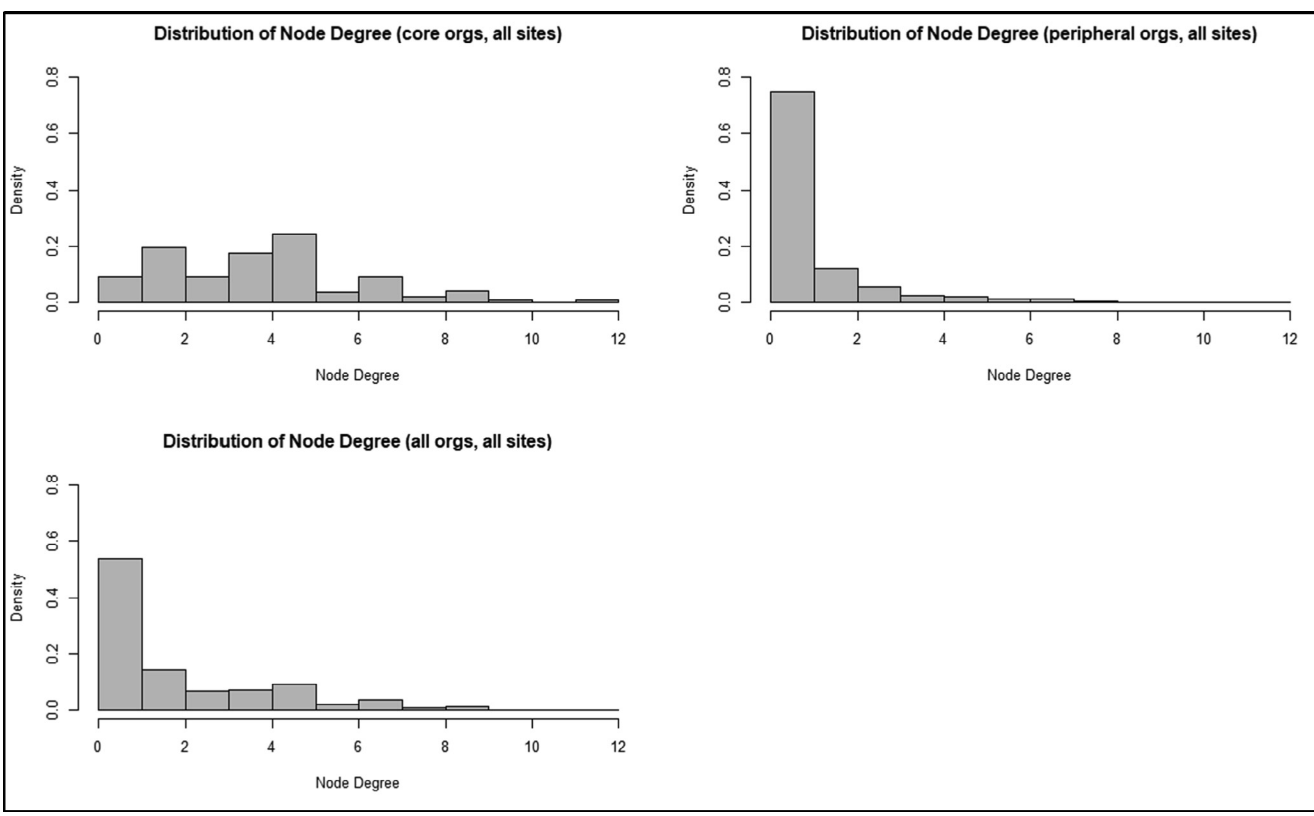


Fig. 4. Plots show degree distributions of (a) core nodes across all sites (top left), (b) peripheral nodes-that were removed from final analysis-across all sites (top right), and (c) all nodes across all sites (bottom left). Comparing degree distributions show that core organizations have a move even degree distribution, with a greater overall number of high-degree nodes (average degree of core nodes across all sites = 4.20). Peripheral nodes have a left-skewed distribution toward a greater number of low-degree nodes (average degree of peripheral nodes across all sites = 1.56).

Table 4
Comparison of full and core networks for each site, providing network graphs and network statistics. Full networks show core organizations (nodes colored by organization type) and peripheral organizations (smaller, uncolored nodes), while core networks remove all peripheral organizations and their ties. HMPL is harmonic mean path length.

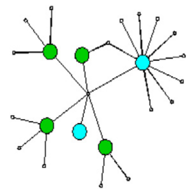
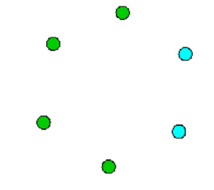
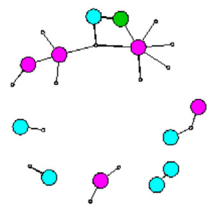
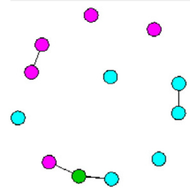
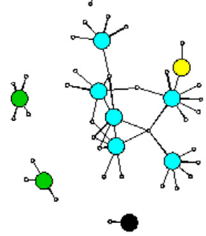
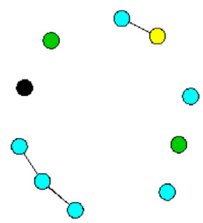
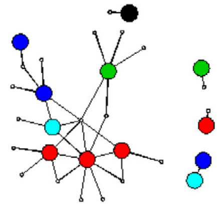
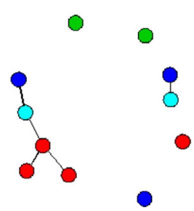
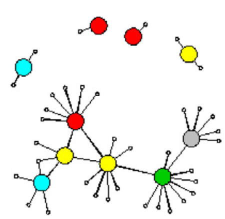
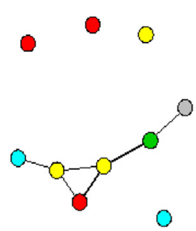
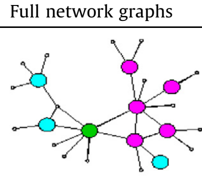
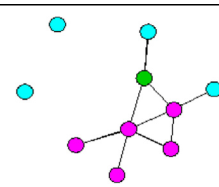
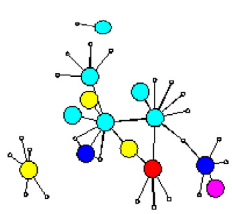
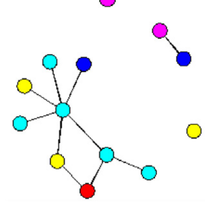
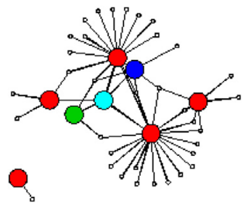
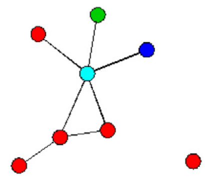
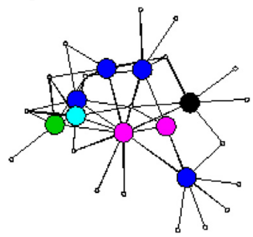
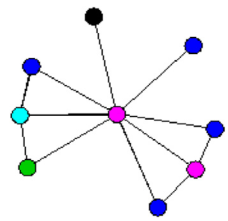
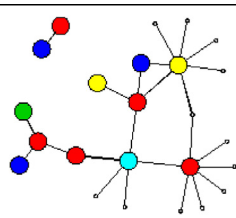
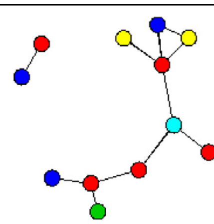
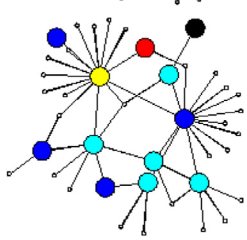
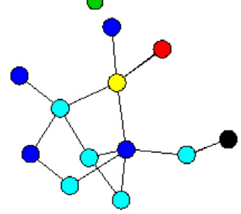
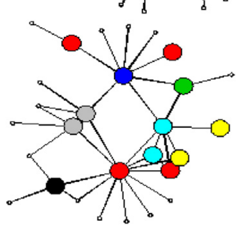
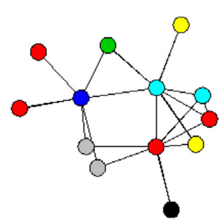
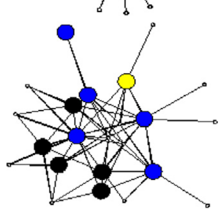
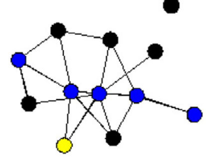
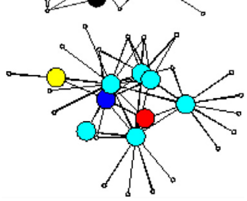
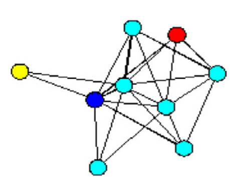
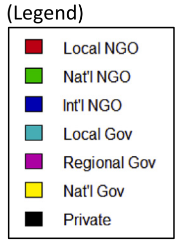
"Fragmented" sites	Full network graphs	Core network graphs	Network statistics	Full	Core
Lushoto, Tanzania			# nodes # components Density Centralization HMPL	24 1 0.09 0.38 2.77	6 6 0 0 NA
Vaishali, India			# nodes # components Density Centralization HMPL	25 6 0.07 0.20 0.71	12 8 0.06 0.15 0.83
Bagerhat, Bangladesh			# nodes # components Density Centralization HMPL	43 4 0.05 0.15 1.90	10 7 0.07 0.19 0.1
Kollo, Niger			# nodes # components Density Centralization HMPL	29 4 0.08 0.26 1.71	11 6 0.09 0.25 0.31
Hoima, Uganda			# nodes # components Density Centralization HMPL	46 5 0.04 0.19 1.92	10 5 0.13 0.25 0.58
"Brokered" sites	Full network graphs	Core network graphs	Network statistics	Full	Core
Karnal, India			# nodes # components Density Centralization HMPL	27 2 0.08 0.20 2.64	10 3 0.2 0.44 0.29
Rubandehi, Nepal			# nodes # components Density Centralization HMPL	34 2 0.06 0.19 2.18	12 3 0.15 0.47 1.01

Table 4 (*continued*)

"Brokered" sites	Full network graphs	Core network graphs	Network statistics	Full	Core
Lawra-Jirapa, Ghana			# nodes # components Density Centralization HMPL	43 2 0.06 0.44 2.34	8 2 0.25 0.62 1.19
Makueni, Kenya			# nodes # components Density Centralization HMPL	28 1 0.13 0.34 2.49	9 1 0.33 0.86 1.48
"Shared" sites	**Full network**	**Core network**	**Network statistics**	**Full**	**Core**
Rakai, Uganda			# nodes # components Density Centralization HMPL	24 2 0.09 0.24 2.48	12 2 0.17 0.24 1.71
Kaffrine, Senegal			# nodes # components Density Centralization HMPL	41 1 0.06 0.33 2.76	12 1 0.21 0.29 2.13
Segou, Mali			# nodes # components Density Centralization HMPL	28 1 0.10 0.37 2.61	13 1 0.24 0.40 1.85
Nyando, Kenya			# nodes # components Density Centralization HMPL	23 1 0.23 0.45 1.98	11 1 0.33 0.46 1.64
Borana, Ethiopia			# nodes # components Density Centralization HMPL	29 1 0.13 0.48 2.21	9 1 0.61 0.5 1.23

(Legend)



Node color	Organization Type
	Local NGO
	National NGO
	International NGO
	Local Government
	Regional Government
	National Government
	Private Sector

Table 5
Results for H1 on network structural forms. Parametric equivalent ANOVA and Tukey Post-Hoc Differences Test for mean network statistics across all sites and within each network structural form[†]

Network structural form	Number of sites	Mean network size	Mean number of components	Mean density	Mean degree centralization	Mean geodesic distance[‡]
All sites (14)	14	10.4	3.36	0.20	0.37	4.43
Fragmented[a] (5)	5	9.8	6.40	0.07	0.17	6.91
Brokered[b] (4)	4	9.8	2.25	0.23	0.60	5.20
Shared[c] (5)	5	11.4	1.20	0.31	0.38	1.85
ANOVA p-values with Tukey Post-hoc Differences	–	–	$p < 0.001^{***ab, ac}$	$p < 0.05^{*ab}$	$p < 0.05^{*ab, ac, bc}$	–

† Statistical significance is indicated for means within structural forms[a,b,c] that were significantly different from other forms ($^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, ‘$p < 0.1$).
‡ Average geodesic distance is calculated as harmonic mean path length, to correct for errors from undefined path lengths in highly fragmented networks.

Table 6
Mean node degree of all organizational types, across all sites and separated by network structural form[†]. Node degree is used for H2 hypothesis on organizational position.

	Mean node degree						
Network structural form	Local NGO	National NGO	INGO	Local gov.	Regional gov.	National gov.	Private sector
All sites	1.93	0.87	2.50	2.11	2.15	1.69	0.75
Fragmented	1.00	0.40	0.67	0.67	0.60	1.75	0
Brokered	1.50	2.00	1.42	2.00	3.13	0.50	1.00
Shared	2.50	1.50	3.43	4.07	N/A[‡]	2.00	1.00

† Average node degree across all nodes and all networks = 1.90. Mean node degrees across organizational types were compared using ANOVA.
‡ No regional government entities were present in any of the shared network sites.

We have shared our data and data analysis tools open access as part of an online Data Profile using Elsevier’s system.

Conflicts of interest statement

We have no conflicts of interest to disclose.

Acknowledgements

The primary data presented in this paper was collected by the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). This work was implemented, in part, as part of CCAFS, which is carried out with support from the CGIAR Trust Fund and through bilateral funding agreements. For details please visit https://ccafs.cgiar.org/donors. The views expressed in this document cannot be taken to reflect the official opinions of these organizations. Additionally, the authors thank the staff at CCAFS for their support of this work and help in organizing and formatting the OBS data to be accessible for our network analysis. We thank Ryan Murphy for his assistance with the graphic design of our figures. We thank CCAFS, the University of California Davis, and the University of Vermont for their support funding the personnel on this project.

Appendix

Appendix I: Comparison of full to core networks

Given the OBS data collection methods, we chose to focus our comparative network analysis around the core networks, which include complete relational data between nodes, rather than at the full network level, where we know there is missing relational data between periphery nodes who were not surveyed themselves for their own relationship data. We describe the OBS collection process and these data analysis decisions in detail in the Methods section in the main text of this paper. This Appendix includes further information on how the removed peripheral nodes compare in degree centrality to the core nodes (Fig. 4) and provides the network graphs and network statistics for the full and core networks for every site, so that readers can evaluate the differences in these two datasets for each site (Table 4).

APPENDIX II: Additional information on methods and results

Network analysis methods

To test *H1* on variation in network structure, we calculated network descriptive statistics including tie density, degree centralization, number of distinct network components (i.e. fragments) and average geodesic distance (Hanneman & Riddle, 2005; Wasserman & Faust, 1994). Given that many of our sites have isolated nodes or components, which complicates traditional average path length calculations which exclude disconnected dyads and thereby would artificially deflate the path length for highly fragmented networks, we use the Harmonic Mean Path Length approximation for average geodesic distance (Newman, 2003). Mean points in these statistics across all fourteen sites were used as the threshold points between “high” and “low” statistic values (e.g. high versus low tie density). These statistics were used to categorize each site into the shared or brokered modes, as defined by Provan and Kenis (2008). We expected to find both shared and brokered networks (Table 5).

After grouping sites by mode, we assessed site and organization-specific attributes. To test *H2* on the roles various organizations play, we first compared the organizational type of the highest degree actor in each site. We also compared the mean node degrees of organizations working at local/regional, national and international scales. For this analysis, we left out the private sector organizations (of which there were only 4 across all sites), because their work scale was not always discernible. We expected to find INGOs with the highest average degree and occupying the most central network position in the majority of sites (Table 6).

Due to small sample size limitations, we used both parametric (Analysis of Variance) and non-parametric (Kruksal-Wallis) statistical difference tests with appropriate post-hoc testing to assess statistical differences and pairwise differences between groups for both H1 and H2 (Shapiro & Wilk, 1965). Results from non-parametric tests are reported in the main text, whereas results from parametric tests are included here in Appendix I.

Table 7
Results for H3 on effect of INGO presence and longevity on network density. Linear regression was used to assess the effect of INGOs on network connectivity, testing for correlation between network density (response variable) and percentage of actors in a network that are INGOs (test a) and longevity of those INGOs in their sites (test b) as predictor variables.

Test	Regression Co-efficient	Regression p-value
Network density ~ % of INGOs (out of all actors in network)	β = 0.34	P = 0.19
Network density ~ average number of years INGo present in network	β = 0.007	P = 0.05

Finally, to test *H3* on the functional roles of INGOs within the network, we evaluated the relationship between the percentage of INGO actors in each site (predictor variable) and the network density and the structural mode of the network in each site (response variables), using both linear regression and Spearman's rank correlation to assess the density relationship. We expected to find a positive relationship between tie density and presence of INGOs and shared network modes in sites with greater INGO presence. Again, results from the Spearman Rank Correlation are reported in the main text, while linear regression results are included here in Table 7.

Network analysis results – parametric statistical tests

Due to small sample size limitations, we used both parametric (Analysis of Variance) and non-parametric (Kruksal-Wallis) statistical difference tests with appropriate post-hoc testing to assess statistical differences and pairwise differences between groups for both H1 and H2 (Shapiro & Wilk, 1965); we used both linear regression and Spearman's rank correlation tests to test H3. Results from non-parametric tests are reported in the main text, whereas results from parametric tests are included here in Appendix II. Directionality of results do not change between the use of parametric and non-parametric statistical tests.

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