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# Putting social networks to practical use: Improving last-mile dissemination systems for climate and market information services in developing countries

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ABSTRACT

Understanding how to improve the accessibility and timely dissemination of weather and market information can help farmers adapt their management to climate change impacts. Our objective is to use Social Network Analysis (SNA) as a tool to identify potential opportunities for improving weather and market advisory dissemination to rural communities and to explore the relationship between farmers' access to information and yield and selling price. As a case study, we applied SNA to 313 farmers in Bangladesh to analyze weather and market information networks and farmers' friendship networks as a potential proxy for information exchange. Farmer access to information, dominant sources of information and potential speed of information transfer were key criteria for our analysis. Our results indicate that weather and market information networks in coastal Bangladesh depended on certain key sources of information, while the friendship network was decentralized and interconnected, with few isolated farmers. We showed that farmers networks are significantly correlated with several socio-agro-economic variables; however, there was little indication of a relationship between information access and yield and selling price. We conclude that a mixed approach of targeting central actors and broadcasting information to farmers may be a suitable strategy to reach a maximum number of farmers as well as the most isolated farmers. Our study highlights that SNA can be a promising tool to reveal hidden structures of information flows in farmer communities and provide valuable insights for developing information dissemination strategies that reach even the most remote and underserved farmers.

## Practical Implications

Access to relevant and timely weather and market information is widely seen as an important factor in increasing farmer resilience to climate change. There is growing interest to better understand how to improve the dissemination of weather and market information to farmers, including the most remote and underserved by information Communication Technologies (ICT). In this study we put Social Network Analysis (SNA) to practical use as a tool to identify potential opportunities for improving weather and market advisory dissemination to rural communities.

As a case study, we examined 313 mung bean farmers in three locations of coastal Bangladesh (Fig. 1). SNA was applied to analyze weather (Wnet) and market information networks (Mnet) as well as informal farmers' friendship networks (Fnet) as a potential proxy for information exchange.

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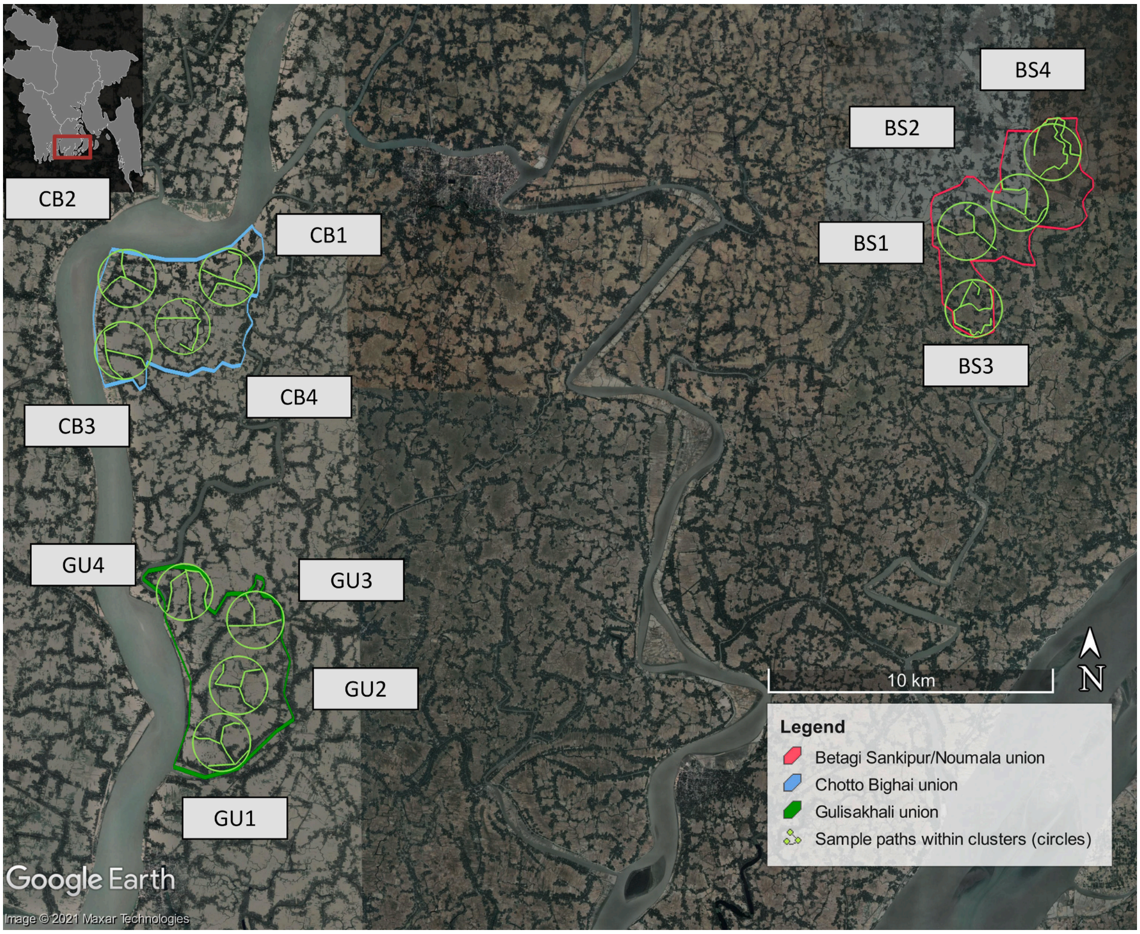



Fig. 1. Map of the sampling clusters in the three unions. Three sampling unions of Chotto Bighai (CB1-4), Gulisakhali (GU1-4) and Betagi Sankipur (BS1-4) with clusters (radius of ~1km2) indicated as red circles and sample paths as red lines in the circle. Sampling followed ideally a Y-shape but in situ followed natural settling structures in the landscape (modified from Google Earth Pro (Earth, 2020)).

To determine which information dissemination strategy to use for a certain region, we first analyzed the farmer communities using SNA. First, interviewed farmers to obtain their weather and market information sources and to name their most important friends among mung bean farmers. We then processed the data into three different social networks, the weather and market information networks and farmers' friendship networks (Fig. 2). Based on social network metrics (Table 1) we gained insights in farmers' information sharing and friendship interaction behavior. SNA helped to assess farmers' access to weather and market information, the most important information sources in a network and the potential speed of information flow through a network.

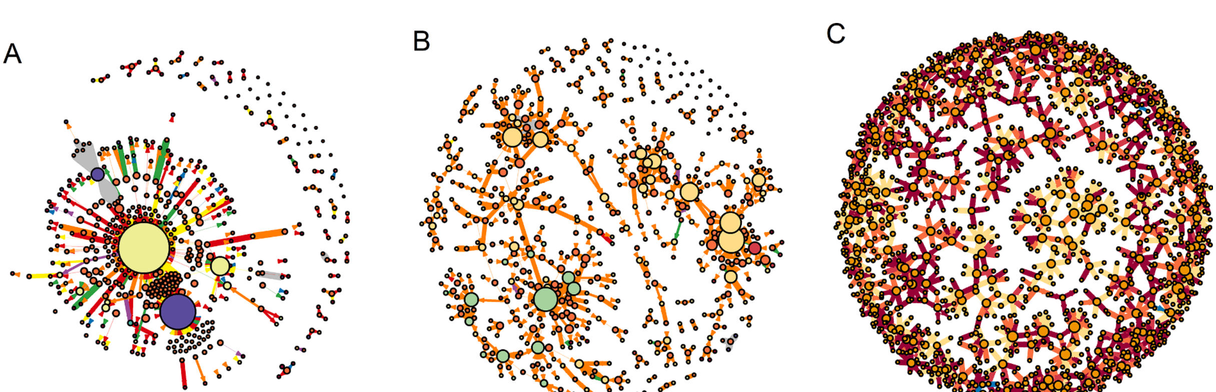


**Table 1. Network metrics with explanations, criteria and relevance**

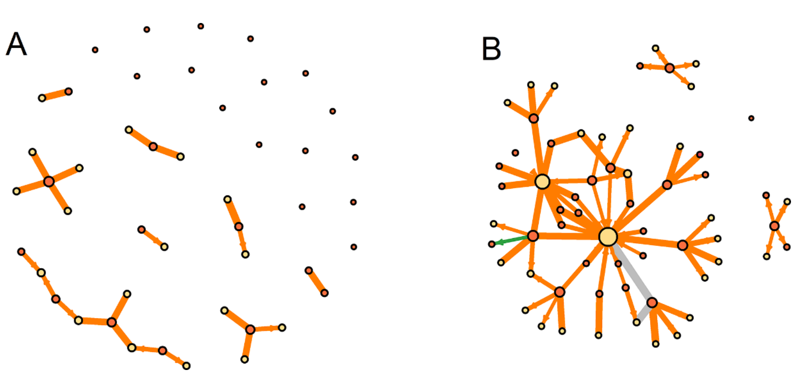
| Network metric | Description | Criteria | Relevance of metrics for the information dissemination process |
|---|---|---|---|
| Outdegree | The number of ties going out of a node in the form of farmers citing an information source. | Access to information | Farmers who cite many information sources have a high outdegree and are assumed to have greater access to information (Aguilar-Gallegos et al., 2015; Aral et al., 2007; Borgatti et al., 2018) |
| Indegree | The number of ties going into a node as an information source cited by farmers. | Source of information | The popularity of an actor as a source of information is defined by their indegree. An actor with a high indegree is cited by many farmers and considered an important information source ( Aguilar-Gallegos et al., 2015; Aral et al., 2007; Borgatti et al., 2018). |
| Degree centrality | Total sum of outdegree and indegree. Number of direct ties that connect to a node (Borgatti et al., 2018). Can be used for network level (average degree) or on node level. | Access to and source of information | Degree centrality can be seen as an indicator of social power and structural influence and can be used to identify an actor's likelihood to access or send information within social networks ( Marsden, 2002). |
| Isolated nodes | Number of actors that are not connected to any other actors (no in- and outdegree). | Access to information | Farmers who do not cite other information sources are considered isolated from the flows of information. |
| Centralization | Indicates how much a single node dominates/controls the flow of information in a network (Freeman, 1978); shows the variability in centrality amongst network actors (Wasserman and Faust, 1994). | Potential speed of information flow & access to information | High centralization means that many farmers are connected to one central actor. Central actors are assumed to be powerful information senders, reaching most of the farmers in the network (Borgatti et al., 2018). With increased centralization, the geodesic distance between the information sender and the farmer accessing the information decreases and thus also potentially the amount of time information needed for the information to diffuse through the network (Freeman, 1978). Low centralization networks indicate an evenly distributed popularity of information providers. |
| Density | Number of ties in a network as a proportion of all ties possible. | Potential speed of information flow | The more interconnected and dense the network, the faster the potential for information dissemination among farmers and other actors (Aguilar-Gallegos et al., 2017). |

Fig. 2. Comparing whole networks based on network graphs. (A) Weather information network; (B) Market information network; (C) Friendship farmer network.Once an SNA has helped identify farmers' access to information, key sources of information and the potential speed of information spread, a strategy for improving weather and market information dissemination can be developed.

Firstly, we recommend analyzing geographic differences in access to information since we found considerable differences in network structure between areas, such as in the Mnet between Chotto Bighai 3 and 4 clusters (Fig. 3). To target isolated farmers, development practitioners should determine and focus on the areas that appear to have the least access to market and weather information, expressed by the lowest outdegree and the largest number of isolated nodes (e.g. Chotto Bighai 3). However, if development practitioners aim to reach the maximum number of farmers and not only the most isolated, then we recommend focusing on areas with a high outdegree and few isolated nodes (e.g. Chotto Bighai 4). The network structure in a particular area will thus determine the information dissemination strategy chosen.

Fig. 3 Market information network (Mnet) of the Chotto Bighai 3 (A) and 4 (B) clusters. The two clusters are less than five kilometers apart from each other but show notable differences in network characteristics, such as isolated nodes and centralization. Chotto Bighai 3 has a large proportion of isolated nodes while Chotto Bighai 4 has few isolated nodes and is highly centralized around two main market information senders.

The next step is identifying key sources of information. Areas with high centralization indicate the presence of dominant sources of information, and by calculating the indegree of each node we can identify them at an individual level. These important information spreaders, especially if they are human rather than technological sources like the TV, can be potentially useful and efficient entry points from which information can be injected into and transmitted through a social network (Fig. 4). Such influential individuals can also be called "opinion leaders".



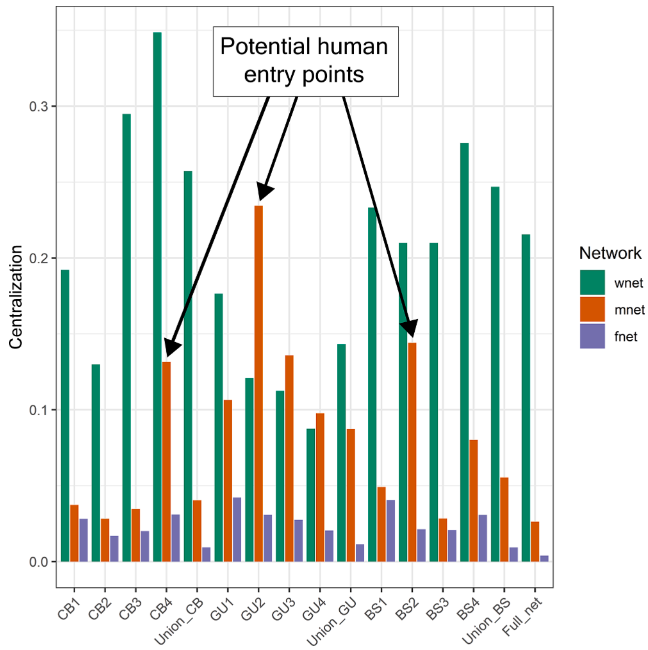



Fig. 4 Identifying human entry points based on social network analysis metrics. Clusters (CB4, GU2 and BS2) with high centralization on nodes that could potentially be targeted by development practitioners as entry points for information dissemination, such as brokers and traders. CB: Chotto Bighai union; GU: Gulisakhali union; BS: Betagi Sankipur union. The number 1-4 indicate the different clusters per union. The "Full_net" shows the aggregation of all three unions.

For example, in our case study, the most important individual human sources of information in the three networks are brokers and input traders. Development practitioners could collaborate with these opinion leaders in order to disperse additional information, such as weather forecasts coupled with agro-advisories. This could be an effective strategy in Chotto Bighai 4, Gulisakhali 2 and Betagi Sankipur 2 (Fig. 4), as most farmers are connected to the central actors (Fig. 3B).

However, there are some constraints, namely that utilizing opinion leaders may maximize the spread of information, but could also undermine efforts to reach marginalized farmers who are less connected to central nodes, reinforcing existing asymmetries in power and influence (Diani and McAdam, 2003; Ernstson et al., 2008). Additionally, opinion leaders may have a vested interest in maintaining the status quo, and may not be willing to share information that could help farmers increase their market power at their own disadvantage (Valente, 2012). Another constraint could be that respected figures for agricultural information may not be as effective in driving the diffusion of information in other domains, such as weather (Adrian et al., 2017; Muller and Peres, 2019). Reliance on a few influential actors could also have implications for information resilience, with the whole information service system falling apart if a powerful information provider leaves the network (Borgatti et al., 2018; Newman and Dale, 2005). It is therefore important to be mindful of centralization when designing interventions based on social networks (Valente, 2012).

What then is the solution in more isolated areas, such as Chotto Bighai 3, where centrality is low and there are around 57% isolated farmers that are not connected to key sources of information (Fig. 3A)? As there are no opinion leaders, it may be necessary to widely broadcast information, for example via farmer groups. In this case there would be multiple entry points, and we would make use of the connectivity of the Fnet to further disseminate information via peer exchange Fig. 2C). Thus, for areas with farmers isolated from key sources of information, an alternative could be using the Fnet as a proxy for information distribution. Although the Fnet may not be rapid, it has the potential to reach isolated and underserved farmers.

In summary, our case study in coastal Bangladesh indicates that a mixed strategy of targeting dominant and accessible sources of information in the Mnet or Wnet, plus broadcasting information into the diffuse but highly connected Fnet when no dominant sources exist, has the potential to effectively and rapidly disseminate weather and market advisories. These actions are likely to reach a maximum number of farmers, including those who are most isolated, lack access to ITCs, and may be underserved by extension services.

## Introduction

Changing climate and extreme weather events are increasing challenges to farm productivity and food security in developing countries, with the largest number of food-insecure people expected in South Asia by 2050 (IPCC, 2014; Thornton et al., 2014; Thornton et al., 2009). Higher temperatures are projected to lead to declining crop yields in tropical regions and threaten smallholder farmers' food security and livelihoods (Shukla et al., 2019; Thornton et al., 2014). Access to relevant and timely agricultural information, such as weather and market information, is widely seen as an important factor to increase farmers' capacity to adapt their farm management to climate change impacts (Descheemaeker et al., 2016; Vogel and O'Brien, 2006). Mechanisms that increase access to and the dissemination of weather and market information could, therefore, aid in efforts to foster smallholder farmers' resilience to extreme weather and climatic events in developing nations (Anderson et al., 2015). In southern India, access to short-term weather forecasts (3–10 days) have been shown to be a driver for operational farm decision making on crop planting, management and early harvesting (Nidumolu et al., 2018). In West Africa, farmers receiving weather information responded by adjusting their farming practices (Oyekale, 2015). In this context, having access to weather information resulted in modifications to farm management practices for nearly 75% of those studied. These changes led to an overall increase in yields of around one third for major African crops (e.g., sorghum, peanut, millet). In Senegal, access to precipitation forecast information assisted farmers in changing their sowing dates and adjusting crop varieties (Roudier et al., 2014). Less attention has, however, been paid to the potentially complementary role that provision of both weather and market information may have on smallholder farm management practices and livelihoods.

In the context of developing countries, smallholder farmers may lack access to accurate market price information and may have to rely mainly on personal contact with suppliers or customers at the farmgate (Verhees and Meulenberg, 2004). Such a lack of market information may stymie farmers' efforts to negotiate with buyers and achieve profitable prices or alternative opportunities when selling their crops (Courtois and Subervie, 2015). Market Information Systems (MIS) can improve market functioning through more symmetric dissemination of information to farmers, as well as to other market actors such as traders and brokers (David-Benz et al., 2016). Mobile-based MIS programs in the Sub-Saharan African context have led to a price increase for sold groundnut achieved by farmers when compared to those without access to an MIS program (Courtois and Subervie, 2015; Svensson and Yanagizawa, 2009). Increasing market information can also influence the degree by which farmers are market rather than subsistence-oriented (Nakasone, 2014). Market orientation is widely accepted to have a positive influence on the economic performance of small farms. Therefore, MIS can assist in increasing farmers' profitability by enhancing knowledge, which could improve bargaining power and the revenues accrued at the farm gate.

However, there are several key challenges to delivering actionable weather and market information to smallholder farmers in developing countries. The accessibility of climate and market information is an important issue and can be hampered by poor infrastructure and lack of access to Information and Communication Technologies (ICTs) such as computers, smartphones or TV. Poor accessibility to information limits the number of farmers that can be reached and the adoption of agro-advisories, especially for farmers living in remote locations (Vogel and O'Brien, 2006). And even if areas have ICT access, TV and radio might not give the most location-specific information (Doblas-Reyes et al., 2003). Another key factor is the timeliness of information, as delays can cause farmers to miss windows of opportunity for critical interventions such as planting, harvesting and disaster prevention (Doblas-Reyes et al., 2003; FAO, 2017). Therefore, there is growing interest amongst agricultural climate service programs that have developed useful climate and market information to better understand how to improve the accessibility and timely dissemination of weather and market information to even the remotest farmers.

In this study, we apply Social Network Analysis (SNA) to analyze and visualize weather and market information flows. SNA can aid in revealing hidden structures related to the exposure to and control of information by social actors and can provide valuable insights for improving information systems (Haythornthwaite, 1996). SNA considers actors called nodes (e.g., individuals, TV) with specific roles (e.g., a farmer, agricultural input dealer) (Borgatti et al., 2009). These actors are linked to each other through ties indicating information exchange between individuals. Network theory is based on the assumption that an actor's position in a network is linked to certain attributes, such as social and economic status, interests, values and beliefs (Andrews and Burt, 1995; Borgatti et al., 2018). Being aware of an actor's position in a network and their attributes can enable information providers to analyze and identify the most effective and efficient ways to disseminate information within a network (Scott, 1988; West et al., 1999).

SNA is widely applied in disciplines such as social media and marketing, and, in recent years, has started to be utilized in a number of agricultural studies (Abid et al., 2017; Aguilar-Gallegos et al., 2017; Lubell et al., 2014; Othieno, 2016). Adger et al. (2016) state that social networks play an essential role in helping rural communities adapt to climate change and weather-related hazards by facilitating the flow of information and enhancing decision making. A study by Matous and Todo (2018) determined that interventions that increased social connections and fostered social learning between farmers increased the adoption of recommended practices. Therefore, it is critical to understand through which channels information does or does not flow to farmers, especially those in remote areas, in order to determine how information dissemination could be improved. We consider that SNA can be used as a tool to analyze this information flow in order to make use of social networks by tailoring interventions that can reach the maximum number of farmers, as well as the most isolated farmers. This paper aims to contribute to the growing field of SNA in agriculture by analyzing the flow of climate and market information dissemination in order to identify potential opportunities for improving weather and market advisory dissemination to rural communities and remote and underserved farmers in developing countries.

The research was conducted via a case study on information delivery systems in mung bean farmer communities in coastal Bangladesh. The large population size and a high poverty rate aggravate Bangladesh's sensitivity to climate change (Rahman et al., 2012). With a total land area of 147.5 km$^2$ and a population size of around 165 million inhabitants (BBS, 2019), Bangladesh is the most densely populated "mega" country (>100 Mio inhabitants) (Streatfield and Karar, 2008). Bangladesh's poverty rate is 23%, with 13% facing extreme poverty (BBS, 2019). Bangladesh's deltaic nature, the low-elevation and the position in the Bay of Bengal render the country vulnerable to floods, cyclones and extreme weather events. The Global Climate Risk Index lists Bangladesh as one of the most vulnerable countries to climate change worldwide (Kreft et al., 2017; Rahman et al., 2012).

Mung bean (*Vigna radiata* L.) is an essential ingredient in many Bangladeshi dishes and widely eaten as *dhal*. Mung bean production is increasingly popular among smallholder farmers in coastal Bangladesh. The Department of Agricultural Extension estimates that 216,509 ha within Barisal Division in Bangladesh's coastal region were devoted to mung bean in 2020, a near 50% increase compared to five years prior. Mung bean producers, however, experience substantial yield and income fluctuations due to yield losses induced by extreme-weather events. These losses are estimated to range from 30 to 90% (from 2016 to 2018) (Krupnik et al., 2020). Most losses result from sudden and heavy rainfall events in the early pre-monsoon season that cause waterlogged fields and seed shattering before farmers are able to fully harvest their crop (Rawson, 2011; Shahrin et al., 2018) (Fig. A.1 and Table A.1 in Appendix). Mung bean is also highly sensitive to high temperature at germination, waterlogging, drought and salinity stress (Singh and Singh, 2011).

Numerous initiatives have focused on the use of ICT to disseminate agricultural climate advisories to farmers in Bangladesh (Chowhan and Ghosh, 2020; Das et al., 2016; Islam et al., 2017; Kafura et al., 2016; Kashem et al., 2010; Khalak et al., 2018; Khan et al., 2017). While mobile phone penetration in Bangladesh is high, close to 100% of the population (BTRC, 2020b), only 62% are subscribed to mobile internet and are smartphone users. Smartphone users are mainly concentrated in urban areas, while remote rural areas can still lack connectivity (BTRC, 2020a). Smallholder and resource-poor farmers may not be able to afford smartphones or data subscription fees (Chowhan and Ghosh, 2020). Studies also indicate inequality in access to ICT, with women having much lower mobile phone ownership rates than men in Bangladesh (Laizu et al., 2010; Stillman et al., 2020). As such, the context in Bangladesh is favorable for exploring how SNA can be used as a tool to overcome the limitations of poor ICT connectivity by identifying effective strategies for 'last-mile' information dissemination to remote areas.

We use an SNA approach to map and visualize weather and market information dissemination networks, as well as farmer friendship networks in coastal Bangladesh. We begin by describing the case study site and outlining the methodologies for the data collection of information networks and crop yields and for conducting the SNA. We then present the results of the SNA for the weather information network, market information network and farmer friendship network at various network levels and geographic units. We also examine whether there is a relationship between farmer access to information and yield and market selling prices. By mapping the structure of the three information networks, we are able to identify i) factors that influence farmers' access to information ii) the main actors and sources of information, and iii) the potential speed of information flow. This enabled us to develop an information dissemination strategy, including identifying suitable entry points into a network. We conclude by providing recommendations for using SNA as a tool to achieve efficient information dissemination and reach a maximum number of farmers, including the most remote and isolated.

## Material and methods

### *Case study site*

The case study area is located in the Patuakhali and Barguna districts in coastal Bangladesh. Three unions (small administrative units) from different polders were selected for the analysis (Table 1). Locations were semi-purposefully selected as communities that could receive future development assistance in the form of climate information services by programs funded by the Embassy of the Kingdom of the Netherlands (Krupnik et al., 2018).

According to the Köppen-Geiger Climate Classification, the study region is categorized as equatorial monsoonal (Am) climate (Kottek et al., 2006). The historical climate of the three unions showed average yearly precipitation of 1955 mm, and a maximum and minimum average daily temperature of 33.3 °C and 12.1 °C, respectively. Patuakhali district's primary sector is agriculture, with rice, pulses, and vegetable as the main crops. 86% of the people in Patuakhali district live in rural areas with a population density of 420 people per km$^2$ (in 2011). Most

**Table 1**
Characteristics of the administrative units (unions) with clusters (1–4), districts, sub-districts and polders related to our study area (BBS, 2014; BBS, 2015).

| Unions (Clusters) | Districts | Sub-districts | Polders | Area ($km^2$) | Coordinates main village |
|---|---|---|---|---|---|
| Chotto Bighai (CB1-4) | Patuakhali | Patuakhali Sadar | 43/2A | 23 | 22°18′48.04″N 90°14′37.22″E |
| Gulisakhali (GU1-4) | Barguna | Amtali | 43/2F | 23 | 22°13′6.87″N 90°16′17.55″E |
| Betagi Sankipur (BS1-4) | Patuakhali | Dasmina | 55/2A | 21 | 22°20′44.72″N 90°31′27.42″E |

are Muslims (93.02%) followed by Hindus (6.87%), Buddhists (0.09%) and Christians (0.02%). Only half of the rural population in Patuakhali district are literate at the age of 7 (BBS, 2015). With regards to natural hazards, the Pyra river borders the length of the north and west borders of Gulisakhali and Chotto Bighai unions and can cause floods. The population density in Amtoli is 376 people per $km^2$ (BBS, 2014).

*Data collection and research design*

We collected data from the three unions in a cross-sectional design (Ott and Longnecker, 2016). Per union, four sample clusters were defined from which around 4 × 25 samples were taken (~100 farmers per union). This resulted in a total sample size of 313 farmers for all three unions. We defined sample clusters (1 km radius) and starting points for enumerators with Google Earth Pro combined with local knowledge (Earth, 2020). Each sampling circle had one starting point (e.g., rural market or primary school) from which enumerators spread out to interview farmers in three different directions following a Y-sampling method (Tittonell et al., 2010). In each direction, we interviewed around eight farmers for each 1 km distance (Fig. 1).

Due to high population density, which obscured obvious social network boundaries such as clearly delineated villages, our social network analysis followed an ego-network approach (Marsden, 2005). The first part of the ego-network approach is the 'name-generator', where farmers (egos) cite their information sources to produce a list of sources (alters). The egos were free to choose the type and number of alters they wanted to cite. Applying the name-generator technique implies less sharply defined network boundaries compared to other SNA methods, where egos are limited to a predefined set of alters in a known network. Using the name-generator method affects the behavior of whole network metrics like the centralization and density and even prohibits the use of certain metrics completely (Borgatti et al., 2018). However, we chose the name-generator technique for three reasons: first, there was no census data nor a complete list of mung bean farmers from which we could obtain a representative sample, neither would we have known how to locate the farmers. Second, the snowballing technique, where each alter cited is subsequently interviewed, or the listing technique, where predefined alter-lists are used, would both have been infeasible given the high population density and the lack of clear boundaries in the scattered and highly populated landscape of coastal Bangladesh (Borgatti et al., 2018). Third, the name-generator method is the most widely used sampling technique in the SNA agriculture literature (Aguilar-Gallegos et al., 2017).

In the next step of the ego-network approach, namely the 'name-interpreter', farmers provide attributes (node and tie characteristics) for each of the cited alters (Aguilar-Gallegos et al., 2017; Borgatti et al., 2018). We interviewed farmers in teams of two local enumerators and pre-tested the semi-closed-ended questionnaire in all three unions. Each enumerator team was assigned to one union. All enumerators were thoroughly trained beforehand to ensure homogenous data quality in the different unions. Collected variables included information on household composition, ICT access, agronomy, weather and market information and friendship networks. In Table 2, we show the social network questions with their respective underlying implications.

To link farmers' position in the information network to agricultural performance, we measured mung bean yields of each interviewed farmer from up to three harvest pickings in April and May (Fig. A.1, Table A.1). The largest mung bean plot per interviewed farmer was selected for sampling. For each farmer field, we installed five sampling

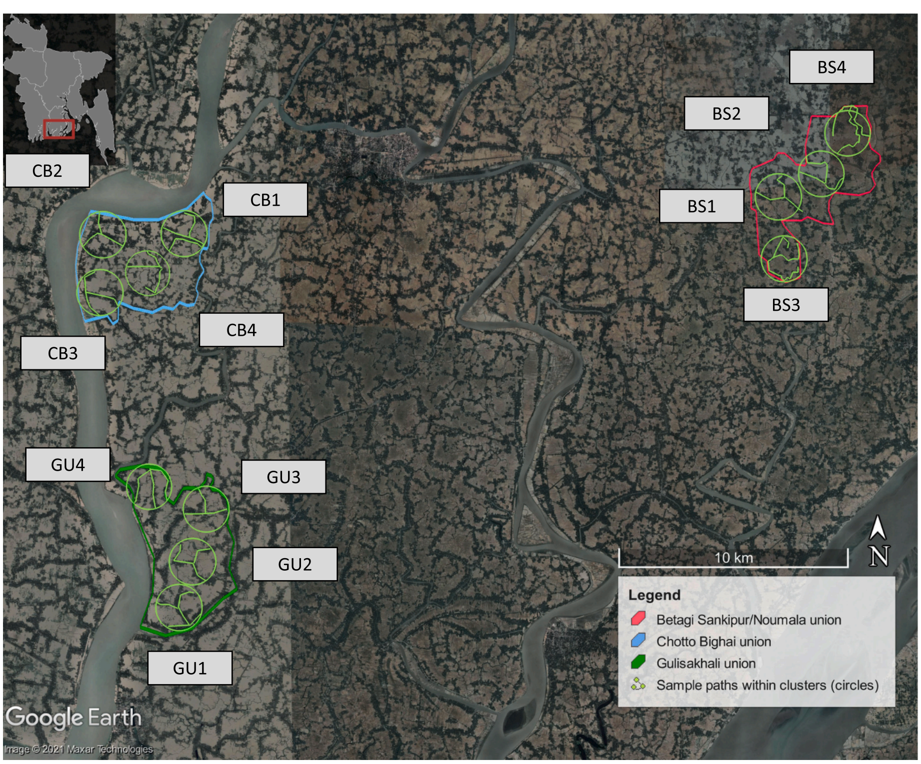



**Fig. 1.** Map of the sampling clusters in the three unions. Three sampling unions of Chotto Bighai (CB1-4), Gulisakhali (GU1-4) and Betagi Sankipur (BS1-4) with clusters (radius of ~1 $km^2$) indicated as red circles and sample paths as red lines in the circle. Sampling followed ideally a Y-shape but in situ followed natural settling structures in the landscape (modified from Google Earth Pro (Earth, 2020)). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

**Table 2**
Social Network Analysis (SNA) questions for the three networks with underlying implications.

| Network | SNA questions | Implications |
|---|---|---|
| Weather information network (Wnet) | Who do you seek advice from when looking for information about weather trends and forecasts related to mung bean farming? | *Trust* in the competence of the cited source for weather and market information (Lyon, 2000). |
| Market information network (Mnet) | Who do you seek advice from when looking for market information on trends and prices related to mung bean selling? | |
| Friendship interaction network (Fnet) | Please list the most important friends you have among mung bean farmers? | When citing someone as a friend among mung bean farmers, it implies trust and intimacy to the relationship (ego-alter). With the term "most important", the most relevant farmer friends are aimed to be detected (positive deviance) (Clancy, 2010). |

frames (each 1 $m^2$) which were randomly distributed in the fields and left there throughout the harvesting season. After harvest, we sun-dried the pods for at least five days and threshed them manually. Then we measured the weight and the moisture content. Seed yield was adjusted at 12% moisture content (Kumar et al., 2013).

### *Data analysis*

A number of metrics have been developed to describe the structural characteristics of networks and the positions that actors occupy within the networks (Hanneman and Riddle, 2014). Social network data was systematized by creating a node catalogue with unique names of all actors, IDs and their node attributes. Further, an 'edge list' was created, defining all the relationships between ego and alters, including their tie attributes (Aguilar-Gallegos et al., 2017). The networks were aggregated for all three unions together, per each union and per cluster levels.

#### *Network metrics*

Five indicators were selected to understand farmers' access to information, their key sources of information, and potential speed of information flow (Table 3). 'Access to information' was quantified by looking at the average number of information sources cited (outdegree), the number of farmers not connected to any information sources (isolated nodes), as well as the dominance of certain actors in disseminating information (centralization). 'Key sources of information' were identified by analyzing the number of times an actor was cited as an information source (indegree). In this study, a person who accessed comparatively more information was indicated by 'high outdegree.' In contrast, an actor with a 'high indegree' acted as an influential sender of information. Therefore, the arrows in the graphs point towards the actors that were cited by farmers as an information source, not the direction of the information flow. 'Potential speed of information flow' was analyzed by assessing the level of interconnection of a network (density) and centralization, as well as tie attributes characterizing the frequency of communication. We did not relate speed to flow in time, but rather in terms of accelerating the dissemination process through social network structures.

#### *Network graphs*

We generated network graphs, displaying nodes and their tie attributes. Node sizes represent the degree centrality of an actor, while the color indicates the role of the respective node. The tie width demonstrates the frequency of communication/interaction, while the color shows the channel of communication. Based on farmers' responses, the derived networks were 'directed', indicated by the arrow pointing towards the source of information. Even though 'own perception' is the farmer citing themselves rather than a separate actor, we depicted it as an individual node to analyze the importance of self-reliance in the whole network. All SNA was conducted using the 'igraph' package in R (Csardi and Nepusz, 2006; R, 2020).

**Table 3**
Network metrics with explanations, criteria and relevance.

| Network metric | Description | Criteria | Relevance of metrics for the information dissemination process |
|---|---|---|---|
| Outdegree | The number of ties going out of a node in the form of farmers citing an information source. | Access to information | Farmers who cite many information sources have a high outdegree and are assumed to have greater access to information (Aguilar-Gallegos et al., 2015; Aral et al., 2007; Borgatti et al., 2018). |
| Indegree | The number of ties going into a node as an information source cited by farmers. | Source of information | The popularity of an actor as a source of information is defined by their indegree. An actor with a high indegree is cited by many farmers and considered an important information source ( Aguilar-Gallegos et al., 2015; Aral et al., 2007; Borgatti et al., 2018). |
| Degree centrality | Total sum of outdegree and indegree. Number of direct ties that connect to a node (Borgatti et al., 2018). Can be used for network level (average degree) or on node level. | Access to and source of information | Degree centrality can be seen as an indicator of social power and structural influence and can be used to identify an actor's likelihood to access or send information within social networks ( Marsden, 2002). |
| Isolated nodes | Number of actors that are not connected to any other actors (no in- and outdegree). | Access to information | Farmers who do not cite other information sources are considered isolated from the flows of information. |
| Centralization | Indicates how much a single node dominates/controls the flow of information in a network (Freeman, 1978); shows the variability in centrality amongst network actors (Wasserman and Faust, 1994). | Potential speed of information flow & access to information | High centralization means that many farmers are connected to one central actor. Central actors are assumed to be powerful information senders, reaching most of the farmers in the network (Borgatti et al., 2018). With increased centralization, the geodesic distance between the information sender and the farmer accessing the information decreases and thus also potentially the amount of time information needed for the information to diffuse through the network (Freeman, 1978). Low centralization networks indicate an evenly distributed popularity of information providers. |
| Density | Number of ties in a network as a proportion of all ties possible | Potential speed of information flow | The more interconnected and dense the network, the faster the potential for information dissemination among farmers and other actors (Aguilar-Gallegos et al., 2017). |

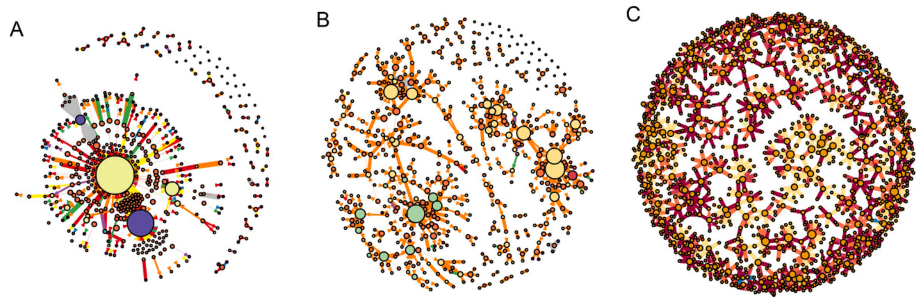



**Fig. 2.** Network graphs for the whole case study area. (A) Weather information network (Wnet); (B) Market information network (Mnet); (C) Friendship farmer network (Fnet). For color legend, see Fig 5.

*Statistical analysis*

We used simple linear regression and Pearson's correlation to analyze the relationships between variables. Outliers above the 75th or below the 25th percentile by a factor of 1.5 times the interquartile range were removed. We compared groups statistically using the non-parametric Kruskal-Wallis test by rank and performed pairwise comparisons using the Wilcoxon rank sum test. Bonferroni was used as a conservative method to adjust the p-value. The significance level was defined as $\alpha = 0.05$. All analysis was done in R (R, 2020).

## Results

### *Social network analysis*

*Network-level*

Overall, the weather information network ('Wnet', Fig. 2A) showed the highest centralization for our whole case study area, indicating a few dominant nodes acting as sources of weather information to farmers (Fig. 2A, Table 4). The market information network ('Mnet', Fig. 2B) showed a number of central actors, while the friendship interaction network ('Fnet', Fig. 2C) was highly decentralized and distributed. The density of all networks was low, with the Fnet having the lowest value. Density is negatively related to network size, explaining the low density of the Fnet as it had the largest network size. Regarding outdegree, farmers cited on average most information sources in the Fnet, and fewer in the Mnet and the Wnet. The number of isolated nodes was also highest in the Mnet and Wnet, highlighting a larger proportion of farmers isolated from accessing weather and market information compared to the Fnet, which had around half the number of isolated nodes.

We performed a statistical analysis on the network metrics based on the 12 farmer clusters (n = 25 per cluster) (Table 4). Centralization and average indegree of actors were the only metrics that differed significantly ($p < 0.05$) between all three networks due to the large variation in actor popularity. There was a significant ($p < 0.05$) difference in farmer average out- and indegrees between the information (Wnet, Mnet) and the interaction networks (Fnet), suggesting that farmers are highly embedded in friendship networks but are seen as poor sources of both weather and market information at an individual level. Isolated nodes are not significantly different between networks, however, the Mnet showed the lowest average value with the highest standard deviation. This suggests strong differences in how much farmers are isolated from

**Table 4**
Weather (Wnet) and market Information (Mnet) and friendship interaction (Fnet) network metrics of mung bean farmers in southern Bangladesh on aggregated and on cluster level.

| Scale of analysis | Metric | Weather Informationnetwork (Wnet) | | Market Informationnetwork (Mnet) | | Friendship Interactionnetwork (Fnet) | |
|---|---|---|---|---|---|---|---|
| | | Mean | SD | Mean | SD | Mean | SD |
| Aggregated network[1] | Centralization | 0.216 | – | 0.026 | – | 0.004 | – |
| | Density | 0.002 | – | 0.002 | – | 0.001 | – |
| | Average outdegree[2] | 1.7 | – | 2.2 | – | 4.3 | – |
| | Average indegree[3] | 1.1 | | 1.1 | – | 1.0 | – |
| | Network size[4] | 489 | – | 625 | – | 1399 | – |
| | Number of alters[5] | 176 | – | 312 | – | 1086 | – |
| | Isolated nodes | 21 | – | 27 | | 13 | – |
| Clusters analysis[6] | Centralisation | 0.199[a] | 0.080 | 0.092[b] | 0.063 | 0.028[c] | 0.008 |
| | Density | 0.024[a] | 0.008 | 0.020[a] | 0.008 | 0.008[b] | 0.002 |
| | Average outdegree[2] | 1.7[a] | 0.4 | 2.2[a] | 0.6 | 4.3[b] | 1.5 |
| | Average indegree[3] | 0.02[a] | 0.03 | 0.00[a] | 0.01 | 0.22[b] | 0.13 |
| | Average indegree total[7] | 7.6[a] | 1.5 | 1.7[b] | 0.8 | 1.0[c] | 0.1 |
| | Network size | 44.8[a] | 9.8 | 56.1[a] | 9.0 | 118.0[b] | 33.0 |
| | Number of alters[5] | 20 | – | 31 | – | 93 | – |
| | Isolated nodes | 1.3[a] | 1.9 | 0.3[a] | 4.7 | 1.3[a] | 2.3 |

[1]Network metrics were computed for the aggregated network for all geographic units combined. No variation.
[2]How many interviewed farmers cite others on average.
[3]How many interviewed farmers are cited by others on average.
[4]Total number of nodes in each network.
[5]Number of cited people by farmers. Calculated as *network_size – number of interviewed farmers*.
[6]Network metrics were computed based on cluster metrics. n = 12 clusters per network type (Wnet, Mnet, Fnet).
[7]Total indegree without filtering.
[a,b,c] Rowwise comparison: Kruskal-Wallis rank-sum test was used to compare network metrics between the three networks Wnet, Mnet and Fnet. Pairwise comparisons were performed using the Wilcoxon rank-sum test with continuity correction and p adjusted using the "Bonferroni" method. Significance is defined at $P < 0.05$ and indicated with differing lower case superscript letters[a,b,c].

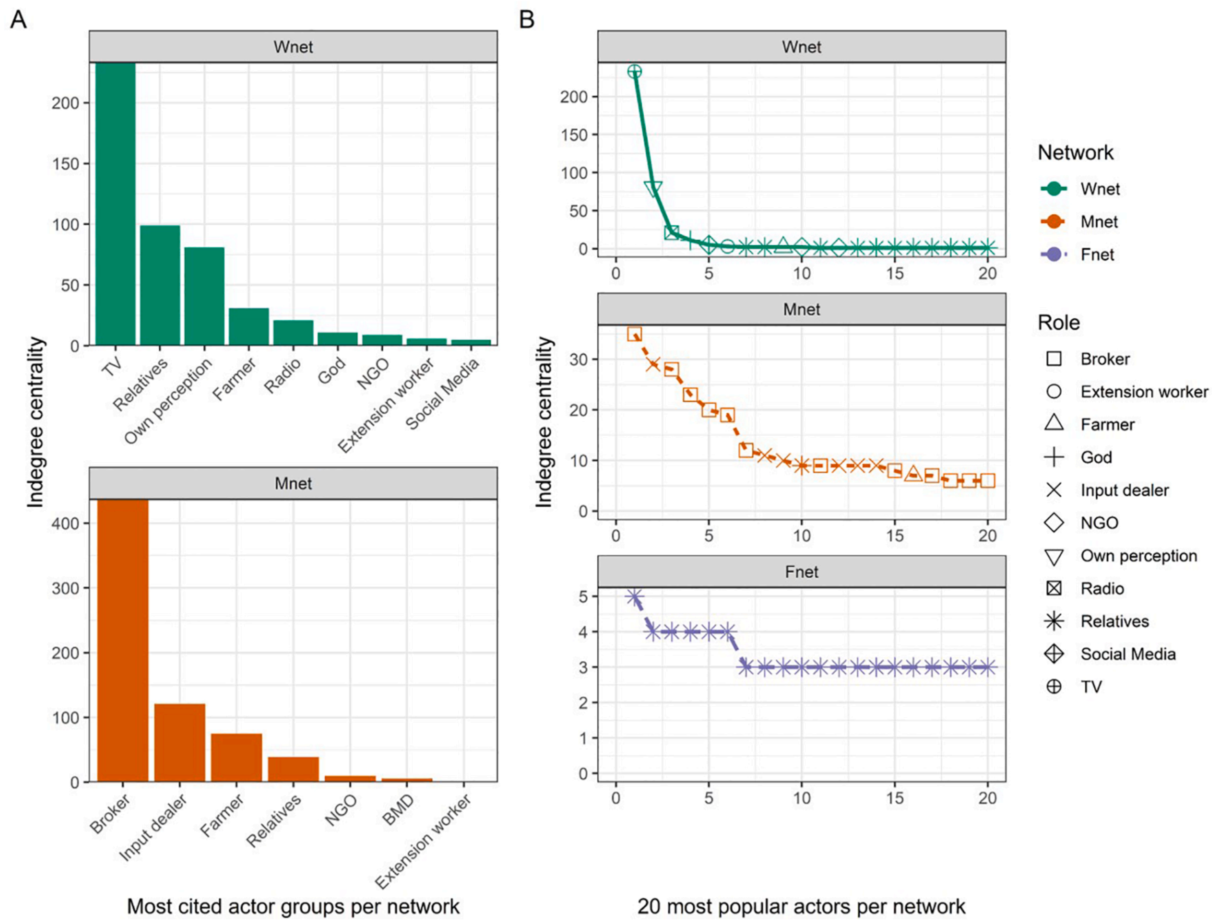



**Fig. 3.** Ranking of the most popular information providers. (A) Indegree centrality is aggregated per actor group and information network (Wnet and Mnet). (B) Ranking of top 20 cited actors with actor's role indicated for the weather and market information and friendship interaction network (Fnet).

market information between clusters in the Mnet.

*Node level*

With regards to the Wnet at the node level, television ('TV') showed a very high indegree of 212 and was by far the most cited information source, followed by farmers' 'Own Perception' (81), 'Radio' (21) and 'God' (11) (Fig. 3B, Wnet). The first human actor, an extension worker, had an indegree of 3, followed primarily by other farmers and relatives with low individual indegrees. The Mnet had the most highly cited human sources of the three networks, which were 'agricultural input dealers' and 'mung bean brokers', the most popular of which had an indegree of 35. In the Fnet, the most cited farmer had an indegree of 5. The dominance of individual nodes in the three networks differed considerably. The Wnet showed a distinct concentration of indegrees on two or three dominant nodes after which there was a sharp decline in popularity. The Mnet demonstrated a steady decline of popularity for the first six actors. The Fnet showed least variation, between 3 and 5 indegrees for the 20 most highly cited sources of information.

When the indegrees of individual nodes were aggregated together by role, TV was still the most important source of information in the Wnet (Fig. 3A, Wnet). However, when grouped together, 'relatives' and 'farmers' had a high total indegree (~100 and ~ 25, respectively), occupying the second and fourth place. In the Mnet, 'brokers' had four times higher total indegree as a group than 'input dealers', followed by other 'farmers' and 'relatives' (Fig. 3A, Mnet). Fnet was not included in panel A as it only represented farmers and relatives.

*Tie level*

At the tie level, the Wnet 'TV' (45%) was the most commonly used channel of information, followed by 'personal communication' with other farmers (23%), and 'mobile phone' (8%) (Fig. 4A). 'Smartphones' were hardly used for weather information. The dominant channel of communication in the Mnet was personal one-to-one communication (97%), with other channels being negligible. The place of information exchange in the Wnet was mainly 'at home' (40%) and 'at market' (30%) (Fig. 4B). 'At market' was also the most common location in the Mnet (54%). For the Fnet, the relationship, or commonality, to the cited source of information was also investigated (Fig. 4C). In most cases commonality was 'neighbors' (42%), 'farmer groups' (25%) and 'relatives' (24%). The frequency of communication with the cited sources of information differed sharply between the three networks (Fig. 4D). The majority of Wnet (59%) and Fnet (78%) interviewees indicated they have 'daily' contact, while the Mnet was most commonly 'every three days' (39%), followed by 'daily' (28%) and 'once a week' (19%).

*Union level*

At the geographic level of the union for the Wnet (Fig. 5), there were no substantial differences in density, isolated nodes and average outdegree between the three unions. The Mnet showed notable differences in the number of isolated nodes between unions, with Chotto Bighai union having the most isolated nodes (Fig. 5B). In the Mnet of the Betagi Sankipur union, 'Input Dealers' had the highest indegree, whereas in Chotto Bighai and Gulisakhali the 'Brokers' were the primary sources of information. For the Fnet, the outdegree differed among unions, with a considerably lower number of citations of friends in Gulisakhali

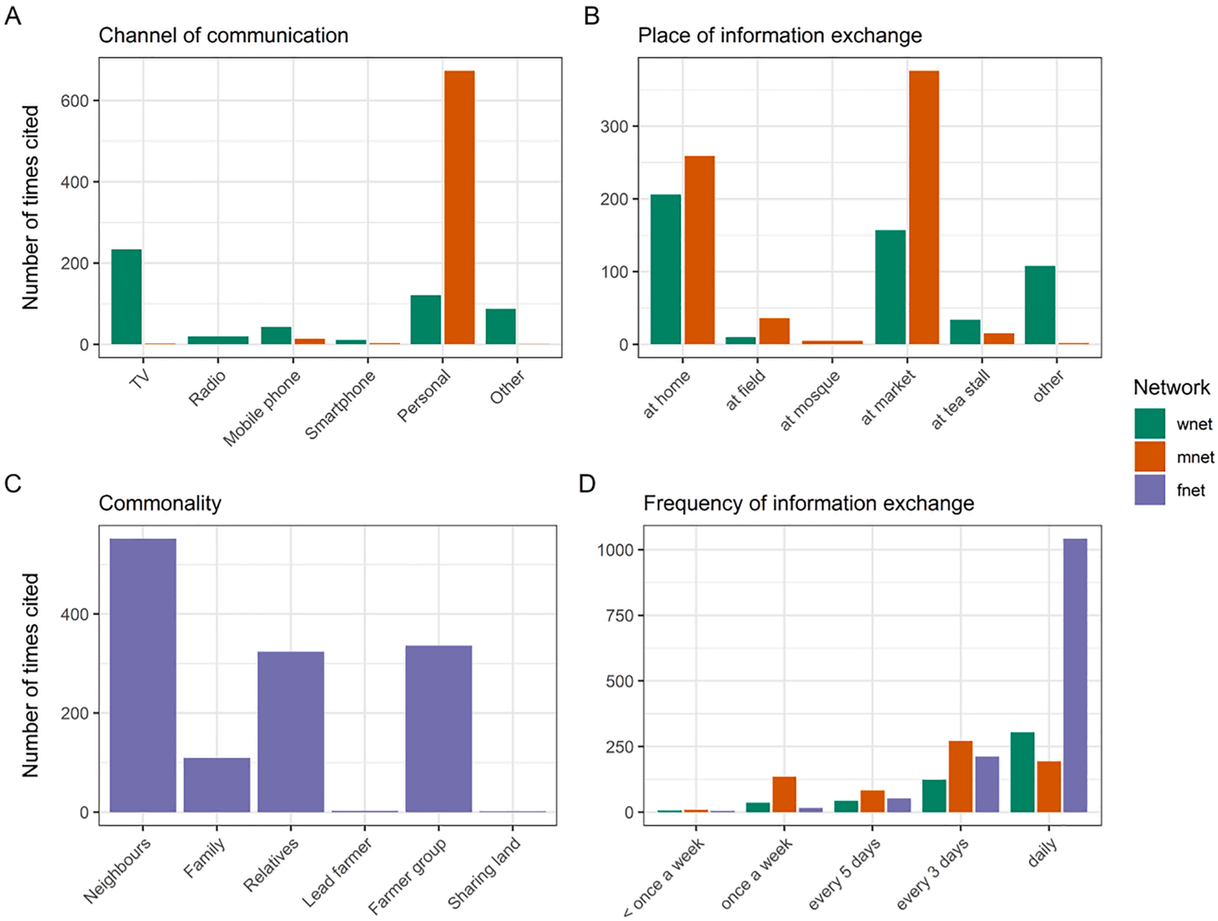



**Fig. 4.** Comparing networks by tie attributes. Tie attributes of weather, market and friendship networks among mung bean farmers in three unions in southern Bangladesh. Panes A-D indicated the number of citations of channels (A), places (B), types of relations (commonality, C) and frequency (D) of communication in the weather, market and friendship networks (Wnet, Mnet and Fnet).

compared to Chotto Bighai and Betagi Sankipur unions (compare Fig. 5F with Fig. 5C & I).

*Cluster level*

In the Wnet at the cluster level, Chotto Bighai 1 and Betagi Sankipur 3 contained the largest number of isolated nodes, indicating low access to weather information (Fig. 6D). In the Mnet, Chotto Bighai 3 had the lowest average outdegree (Fig. 6C), the highest number of isolated nodes (Fig. 6D) and the lowest density (Fig. 6A), implying that the cluster was quite disconnected from market information and has a low potential speed of information flow. In a pairwise comparison of the clusters for outdegree in the three networks, we found that Chotto Bighai 3 was most significantly ($p < 0.01$) deviating from the other clusters in all three networks but especially in the Wnet and Mnet. (Fig. B.1 in Appendix).

On the other hand, Chotto Bighai 4, Gulisakhali 2 and Betagi Sankipur 2 showed very high centralization (Fig. 6B) and density (Fig. 6A), with hardly any isolated nodes (Fig. 6D), suggesting good access to information and a high potential speed of information flow. These differences, such as between Chotto Bighai 3 and 4, which are only 5 km apart, could be clearly visualized in the cluster network graphs for the Mnet (Fig. 7A-B). In the Fnet, the clusters showed less variation in network metrics except for outdegree, where the Gulisakhali clusters had around half the outdegrees as the clusters in the other unions (Fig. 6C and Fig. B.1, C.1–C1.3 in Appendix).

*Farmers' outdegree and mung bean yields and selling price*

To understand the relationship between access to information and farmer productivity and profitability, we analyzed how mung bean yields related to access to weather information, and selling price to access to market information. First, we sought to clearly understand the patterns of mung bean yield and the selling price on cluster level (Fig. 8A-B). In the Chotto Bighai union there was no significant mung bean yield and price difference between clusters ($p < 0.05$). Despite their close geographic location, Gulisakhali 1 and 2 demonstrated strong significant yield difference ($p < 0.001$). In Betagi Sankipur 1 we found the lowest yields of all clusters (Fig. 8A). The mung bean selling price was significantly ($p < 0.05$) lower in Betagi Sankipur union compared to clusters in other regions (except of clusters CB4 and GU2) (Fig. 8B).

No significant relationship between farmers' access to weather and market information and selling price ($P = 0.53$) and yields ($P = 0.81$) were found in our study for all clusters aggregated (Fig. 9A–D). Lowest yields were indicated at an outdegree around 2 and 3, and highest yields with the maximum outdegree values of 4 and 12 for the Wnet and Fnet, respectively (Fig. 9C–D).

Taking a closer look into the cluster level data, we found four clusters that showed a significant relation between farmers' outdegree and mung bean yields and selling price. Gulisakhali 3, had a significant ($P < 0.05$) negative association between famers' outdegree in the Mnet and mung bean price, while in In Betagi Sankipur 4, both outdegree in the Wnet and Fnet were significantly ($P < 0.05$) negatively related to mung bean yields (Fig. 10C-D). Only in Gulisakhali 2 farmers' outdegree in the Fnet was positively related to mung bean price (Fig. 10A-B).

Broadening our analysis, we investigated additional socio-agroeconomic variables collected during the household and field survey. Looking at agronomic variables, we found that mung bean yields

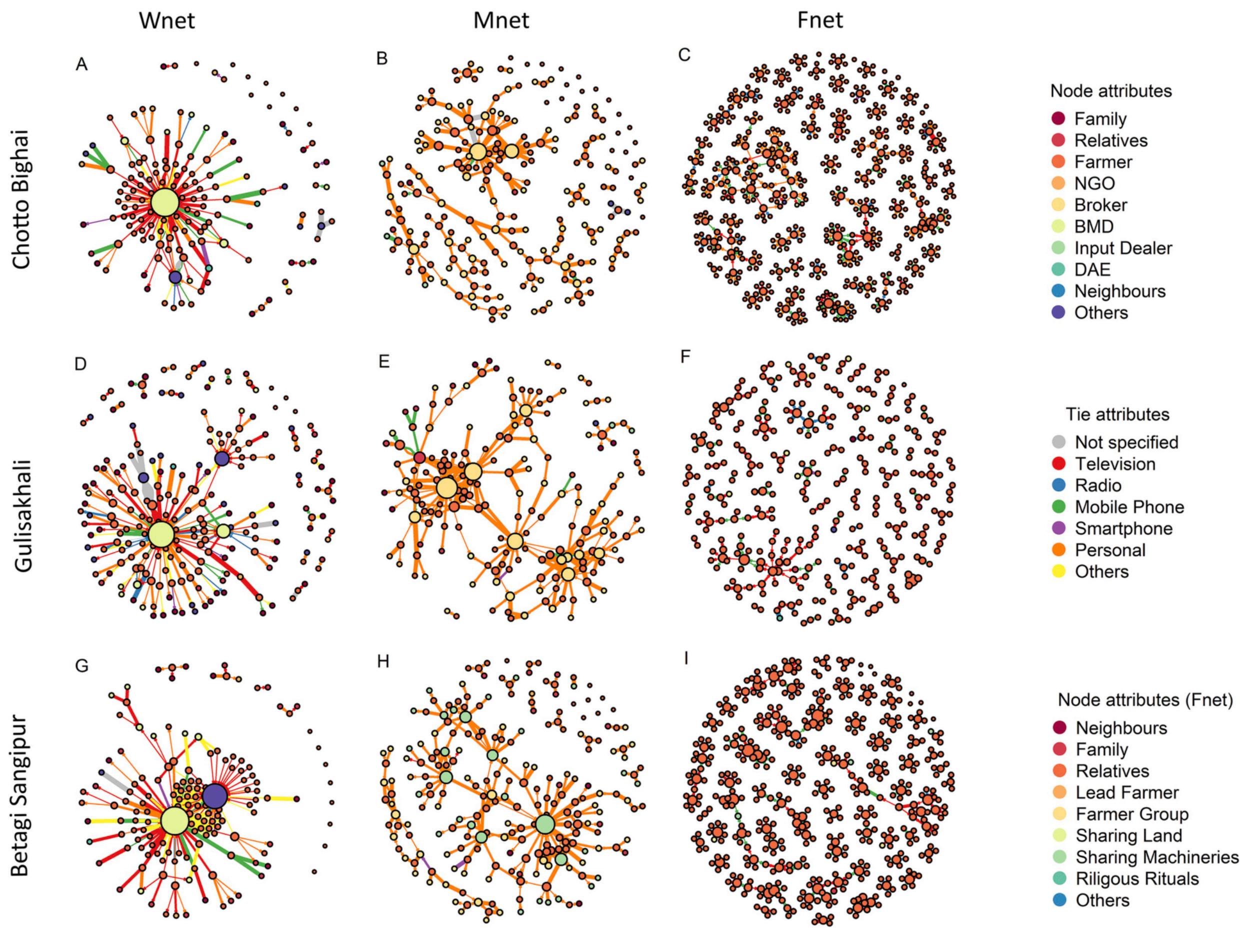



**Fig. 5.** Social networks for the weather (Wnet) and market (Mnet) information and the friendship network (Fnet) among mung bean farmers in three unions of southern Bangladesh. Size and color of the nodes are linked to total degrees and the role of the actors, while the width and color of ties are linked to the frequency and channel of communication, respectively.

were positively related to mung bean plant density ($p < 0.001$) and mung bean selling price ($p < 0.001$), while the number of weeds was strongly negatively related to yields ($p < 0.01$). Regarding network metrics and related variables, we found only one significant ($p < 0.05$) association between yields and farmers' outdegree in the Fnet. When investigating how network metrics correlate among each other, we showed that farmers' outdegree in the Mnet was positively related to farmers' outdegree in the Wnet ($p < 0.001$) and in the Fnet ($p < 0.01$). However, outdegree in the Fnet and Wnet showed no association. With increased distance to the next market, farmers showed lower outdegree in the Wnet ($p < 0.05$) and Mnet ($p < 0.001$), while they showed a significantly higher outdegree in the Fnet ($p < 0.001$). More land under mung bean cultivation correlated with a higher outdegree in Wnet and Mnet ($p < 0.05$). For farmers' outdegree in the Fnet however, it is the total owned land that was positively correlated ($p < 0.01$). Gross income was further positively related to outdegree in the Wnet and Mnet ($p < 0.01$) but negatively for the outdegree in the Fnet ($p < 0.01$). Farmers' outdegree in the Fnet was also positively associated with the years of mung bean experience ($p < 0.001$) (Fig. 11).

## Discussion

The aim of this study was to explore how SNA could be used as a tool to identify potential opportunities for improving weather and market advisory dissemination to rural communities in developing countries. We especially sought to identify key elements and entry points of a 'last-mile' dissemination strategy that not only provides information to the most popular and well-connected farmers, but also to those that are comparatively isolated and have limited access to ICTs.

### *Access to information*

According to diffusion theory (Valente 1996), individuals who are not exposed to information through their network due to not having a mechanism by which to learn new information, may never adopt agro-advisories. Such lack of access to climate and market information is an important issue in remote rural areas that may be underserved by ICTs, as it limits informed decision-making (FAO, 2017). In our case study, the Mnet had the highest number of isolated nodes at the network level, indicating a large number of farmers that are potentially cut off from market information. They therefore may have less knowledge of market prices than farmers who have a higher outdegree and cite more information sources. The Wnet also had a high number of isolated nodes, as well as the lowest average outdegree and a high centralization value. This suggests that a small number of actors were highly cited, and that farmers relied on a limited variety of sources for weather information. The Fnet, however, demonstrated double the average outdegree and half the number of isolated nodes compared to the other networks, implying a high friendship interaction between farmers and only a few peripheral farmers who were disconnected from the network. We were able to gain further information regarding the primary locations and channels through which farmers access information for each of the three networks by analyzing the tie level.

Visualizing information access at various geographic levels, such as the cluster level, enabled us to pinpoint the most connected and disconnected areas. For example, Chotto Bighai 3 and Chotto Bighai 4

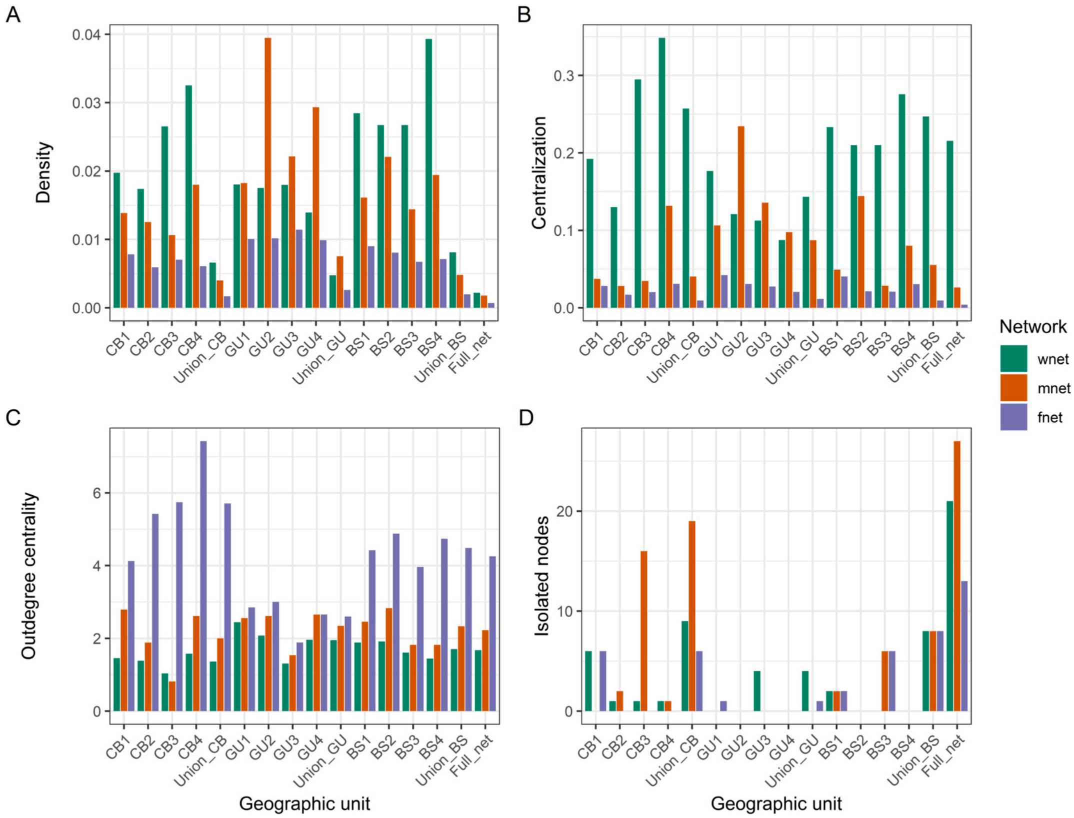



**Fig. 6.** Network metrics of the Weather (Wnet) and Market (Mnet) information and Friendship (Fnet) interaction networks at full, union and cluster level in Chotto Bighai (CB), Gulisakhali (GU), Betagi Sankipur (BS) unions in southern Bangladesh. Within the unions (Reg_), clusters are numbered 1-4. (A) Density, (B) Centralization, (C) Outdegree centrality and (D) Isolated nodes.

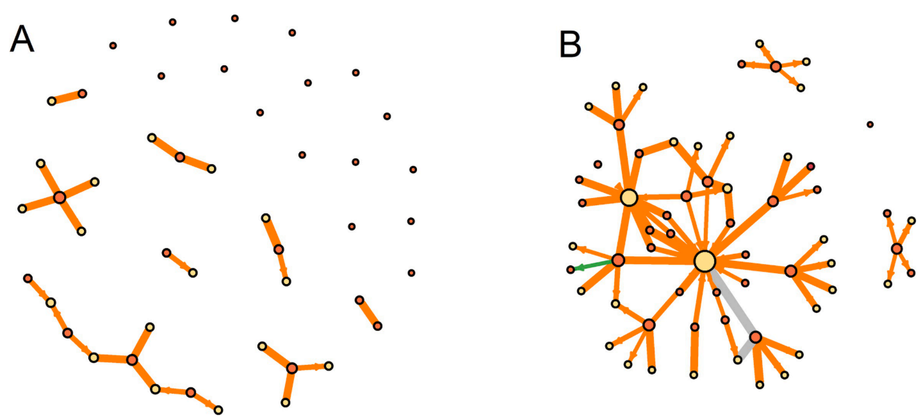



**Fig. 7.** Market information network (Mnet) of the cluster Chotto Bighai 3 (A) and 4 (B). The orange tie color signifies personal communication.

clusters, while neighbors (Figs. 6A-D and 7A-B), differed substantially in information access, highlighting the importance of location-specific dissemination strategies. Thus, by analyzing the number of isolated nodes, average outdegree and centrality, as well as exploring geographic differences, it was possible to get an understanding of farmers' access to weather and market information and the connectivity of the friendship network.

*Sources of information*

Being aware of the key sources of information in a network can help us identify potential entry points for further information dissemination. Wnet had the highest centralization, indicating a few dominant sources of weather of information. However, there were important differences in the Wnet between key sources of information at an individual node level vs an aggregated level. At the node level, TV, own perception and the radio were the dominant individual sources of information, while no individual farmer held an influential position. However, at an aggregated level, peer sharing between farmers was the second most important source of information in the Wnet, indicating that farmers do turn to each other to discuss weather forecasts. Mass media sources like the TV are not ideal for development organizations to target as entry points since, as official news sources, they are challenging to influence. However, peer-to-peer communication between farmers could be potentially harnessed to diffuse information.

The Mnet was also dominated by a few key sources, mainly brokers and input dealers, with a number of highly cited individuals at the node level depending on the area. These brokers and input dealers could be

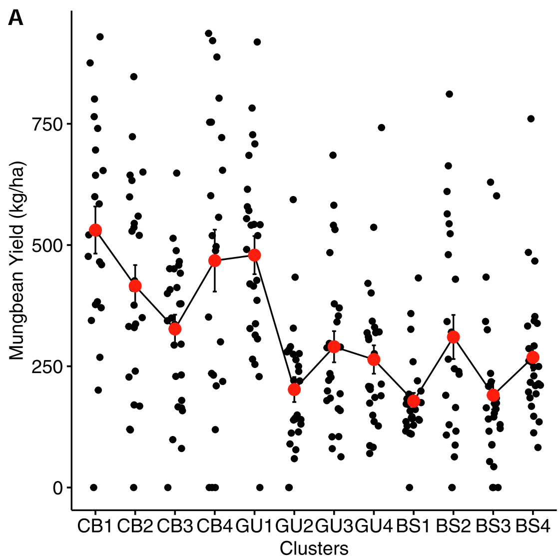



**Fig. 8.** Farmers' mung bean yields (kg/ha) and selling price (USD/kg) per clusters. The black dots indicate the farmers' performance metric (yield, price) per cluster while the red dot indicates the average per cluster.

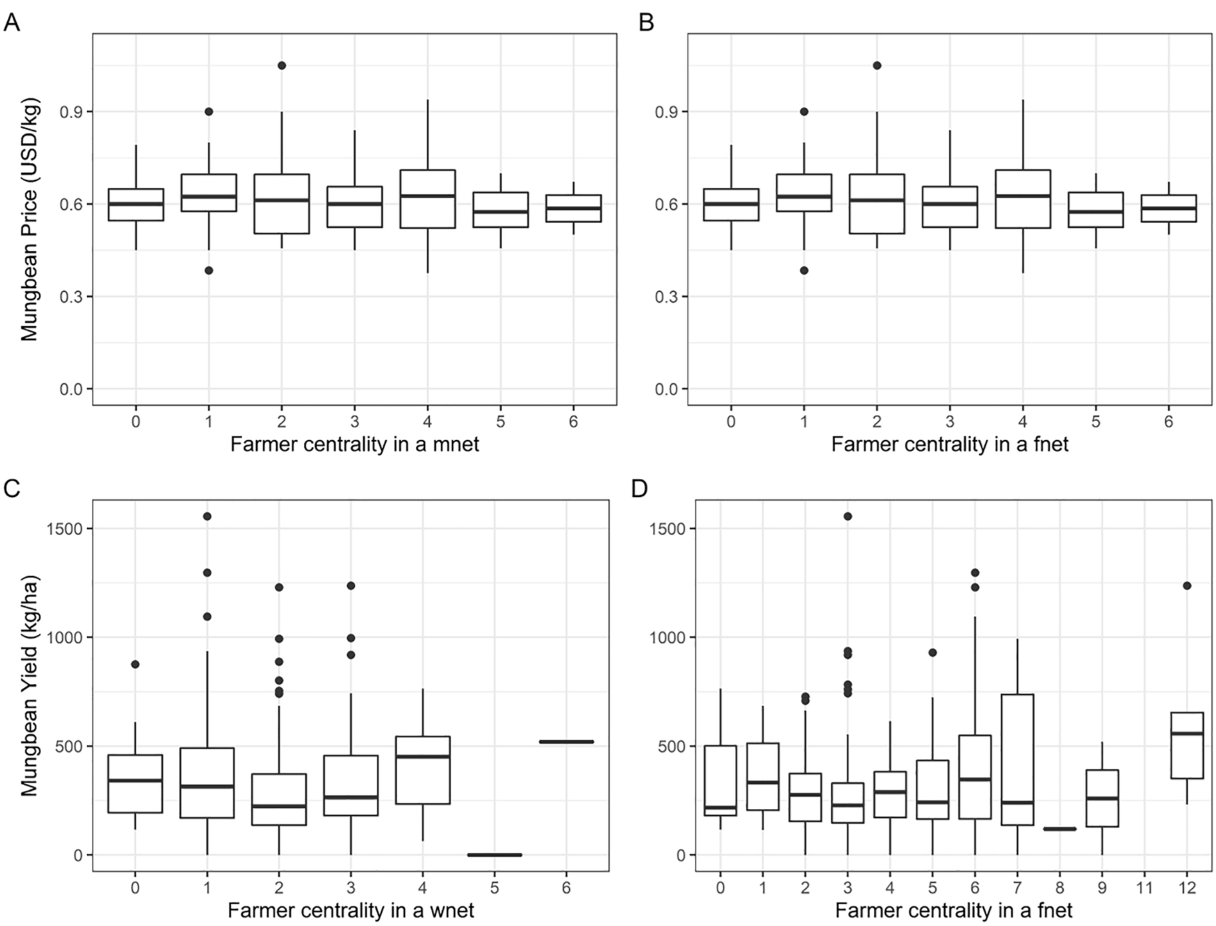



**Fig. 9.** Relation between mung bean farmgate price (A, B) and yield (C, D) and farmers' outdegree in market (A) and weather (C) information and friendship (B, D) networks.

considered "opinion leaders", namely network members that are effective in persuading others and spreading their influence onto large populations (Muller and Peres, 2019). Studies have shown that using opinion leaders to disseminate information speeds up the diffusion process (Valente and Davis, 1999). Therefore, since opinion leaders are important sources of information and are individuals rather than mass media channels, they could be a potential target for disseminating market information. Peer information sharing in the Mnet, however, was much lower than in the Wnet. A possible explanation for low peer-to-peer exchange of market information may be that sharing price

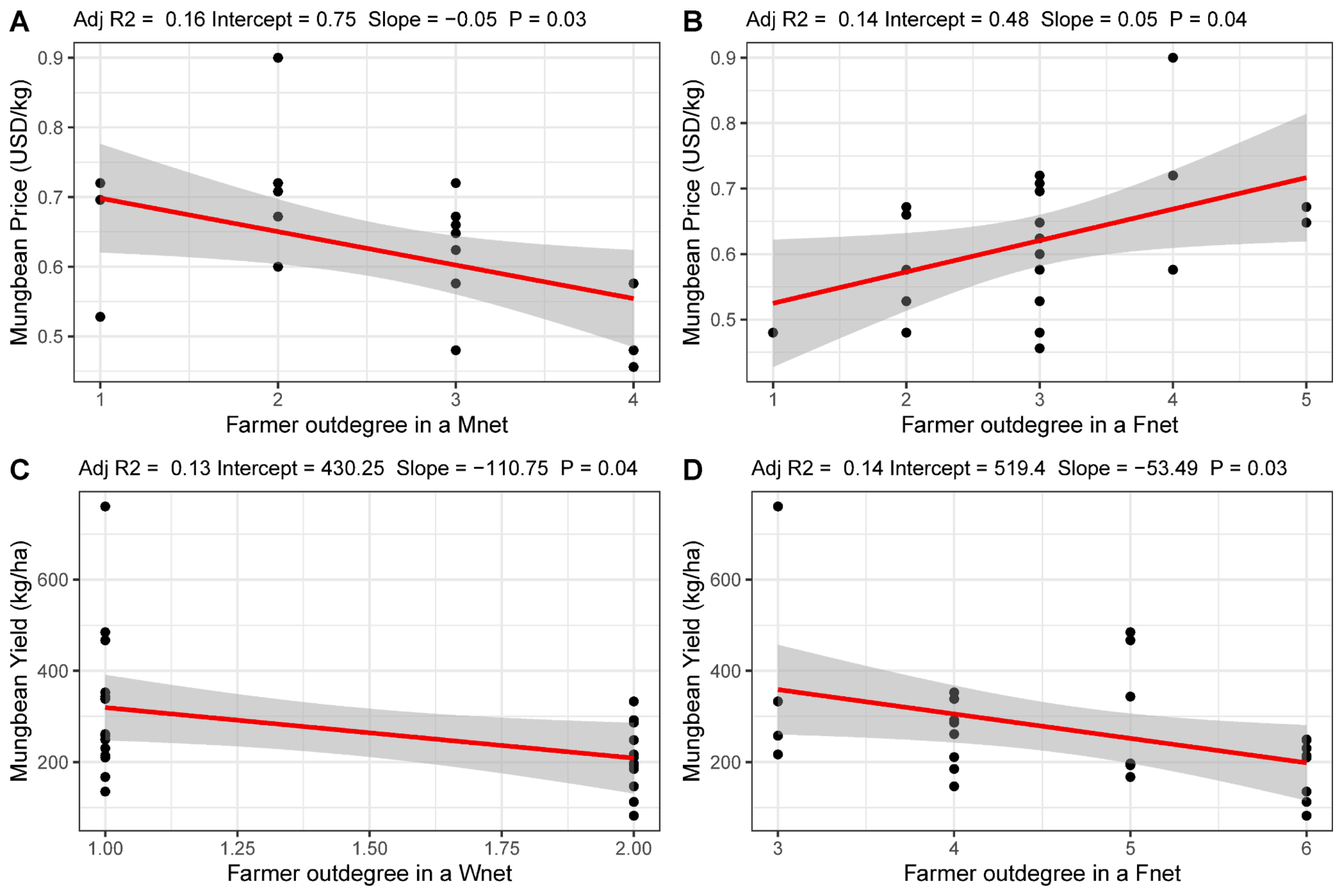



**Fig. 10.** Analysis of clusters with a significant relationship between mung bean price and yield and the outdegree of farmers in the Wnet, Mnet and Fnet. (A, B) Relation between mung bean price and farmers' outdegree in the Mnet and Fnet of the Gulisakhali 2 cluster (GU2). (C, D) Relation between mung bean yields and farmers' outdegree in the Wnet and Fnet of the Betagi Snakipur cluster 4 (BS4). A simple linear model was fitted to the data; Significance at p = 0.05.

information could result in market competition between mung bean farmers (Braguinsky and Rose, 2009; Chen et al., 2015). While this may explain the lack of information exchange, encouraging more transparency around market prices could actually have the opposite effect by allowing farmers to compare offers and increase their bargaining power (Courtois and Subervie, 2015).

The Fnet had low centralization, indicating a lack of key information sources. Consequently, there were no obvious individuals or opinion leaders to target as entry points. However, the Fnet could potentially be used to spread information once it is within the network due to its high connectivity and low number of isolated nodes. Thus, indicators such as centralization at a network level and average indegree at a node level, can help us to determine whether there are dominant sources of information in an area, to identify what or who they are, and to assess whether they could be used as entry points for weather or market information.

*Potential speed of information*

Receiving information rapidly, especially weather information, could help farmers take pre-emptive management action during critical phases of crop production and avoid negative consequences of extreme weather events (Doblas-Reyes et al., 2003). In our case study, we conclude that there was likely fast exchange of weather information in coastal Bangladesh since television, as the central source of information, is able to immediately disseminate information to around 75% of farmers. Information exchange also occurred frequently, mostly daily or every three days, and primarily took place at home (likely television) or at the market (likely peer exchange). The Wnet was also relatively dense due to the low network size, which is considered conducive to rapid information exchange. However, while the structure of the Wnet is favorable to rapid information dissemination, it is questionable whether dissemination speed would be the same if the source of weather information were not the TV.

The Mnet had lower centralization and frequency of communication, primarily every three days through personal communication at the market. We infer that information exchange would be slower and might be limited to market days where farmers can discuss directly with brokers and traders. In the Fnet, information is likely to be shared widely among farmers on a daily basis due to its connectivity and large size. However, the Fnet had no central information spreaders and was the least dense network, suggesting that information exchange may be slow. Thus, centralization, density and frequency of information exchange can provide insights into the potential speed of information dissemination (see Figs. 4 and 6).

*Strategies for information dissemination*

Once an SNA has helped identify farmers' access to information, key sources of information and the potential speed of information dissemination, a strategy for improving weather and market information dissemination can be developed. Firstly, we recommend analyzing geographic differences in access to information, as we identified considerable differences in network structure between areas. To target isolated farmers, development practitioners should determine and focus on the areas that appear to have the least access to market and weather information, expressed by a low outdegree and a high number of isolated nodes (e.g. Chotto Bighai 3). However, if the aim is to reach the

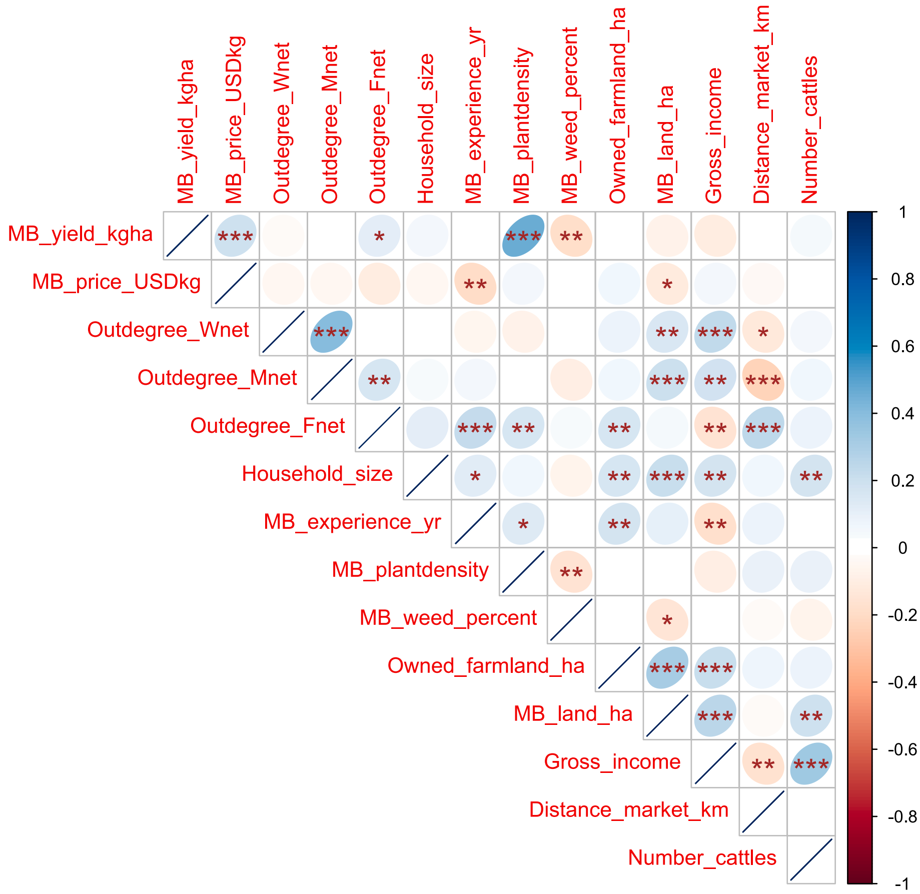



**Fig. 11.** Correlation matrix with farmers' outdegree in the Wnet, Fnet and Mnet, farm productivity and socio-agroeconomic variables. The elliptic shape indicates the positive or negative correlation between two variables while the color indicates the strength of correlation. Asterisks indicate significance levels: * sig. at 0.05, ** sig. at 0.01, *** sig. at 0.001.

maximum number of farmers and not only the most isolated, then we recommend focusing on areas with a high outdegree and few isolated nodes (e.g. Chotto Bighai 4). The network structure in a particular area will then determine the information dissemination strategy chosen.

The next step is identifying key sources of information. Areas with high centralization indicate the presence of dominant sources of information, and by calculating the indegree of each node we can identify them at an individual level. Especially if they are human rather than technological sources like the TV, these sources can be useful and efficient entry points to inject and transmit information into a network. In our case study, the most important individual human sources of information in the three networks were brokers and input traders. Development practitioners could collaborate with these opinion leaders in order to disperse additional information, in line with a growing trend in agricultural research and development to partner with the private sector (Spielman, 2006). This could be an effective strategy in Chotto Bighai 4, Gulisakhali 2 and Betagi Sankipur 2, for example, as most farmers were connected to one central broker (Fig 12).

However, there are some constraints, namely that brokers and input traders may be opinion leaders in one domain, i.e. market information, but may not be as effective in driving the diffusion of information in other domains, like weather (Muller and Peres, 2019). Farmers may not intuitively turn to or consider brokers and input traders as reliable sources of information on the weather.

This strategy may also not be effective in areas with characteristics similar to Chotto Bighai 3, where centrality was low and there were around 57% isolated farmers that were not connected to key sources of information. This is supported by Portes (1998) and Young et al. (2021) classification of network-based intervention strategies, in which utilizing opinion leaders maximizes the spread of information, but could also undermine efforts to reach marginalized farmers who are less connected to central nodes. Thus, distributing information via dominant information sources in a highly centralized network may reinforce existing asymmetries in power and influence (Diani and McAdam, 2003; Ernstson et al., 2008). Additionally, opinion leaders may not always be ideal agents of change as they often have a vested interest in maintaining the status quo – in this case brokers and input traders may not wish to disseminate information that may disadvantage their market position (Valente, 2012). Finally, information resilience, namely the capacity of an information service system to provide a reliable and continuous flow of information amongst a background of fluctuating network actors (Borgatti et al., 2018; Newman and Dale, 2005), is generally thought to be lower if there is reliance on only a few influential actors. If a powerful information provider is removed from the network, for example a broker leaving to another region, the whole information service system could fall apart and famers would be fragmented into single isolated nodes (Borgatti et al., 2018; Newman and Dale, 2005). It is therefore important to be mindful of centralization when designing interventions based on social networks (Valente, 2012). The strength of social network analysis, however, is that it makes such issues explicit and visible and allows for the design of appropriate policies to overcome social imbalances (Fig. 12).

What then is the solution in more isolated and underserved areas where there are no key sources of information, or where using opinion leaders is considered undesirable? In these cases, it may be necessary to widely broadcast information, for example via farmer groups. In this case there would be multiple entry points, and we could make use of the connectivity of the Fnet to further disseminate information via peer

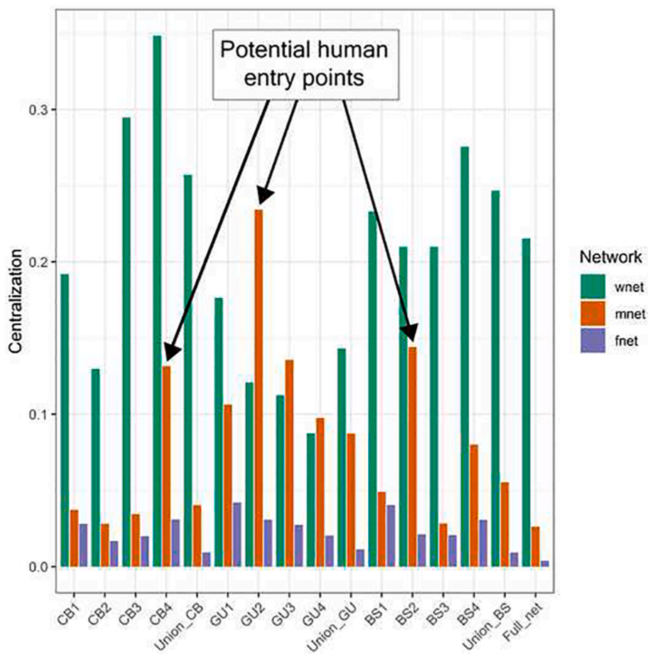



**Fig. 12.** Clusters (CB4, GU2 and BS2) with high centralization on nodes that could potentially be targeted by development practitioners as entry points for information dissemination, such as brokers and traders.

exchange. Thus, for areas with farmers isolated from key sources of information, an alternative could be using the Fnet as a proxy for information distribution. Although the Fnet may not be rapid, it has the potential to reach isolated and underserved farmers. This strategy was supported by evidence that suggested that peer exchange was already an important source of information within the Wnet.

The use of the friendship network as a proxy for information exchange capacity is generally supported by diffusion theory literature, in addition to social network analysis (Borgatti, 2005; Oyekale, 2015), which show friends interacting and exchanging informal information (Gambetta, 2000). One consideration is that information tends to flow more easily among actors who are similar (Aguilar-Gallegos et al., 2015). In our study region, communities had high cultural homogeneity (BBS, 2019), however in diverse communities there may be constraints to peer-to-peer communication. Farmer groups could play a role in enhancing peer-to-peer information sharing capacity by providing opportunities for social interaction, especially if farmers from separate communities come together to exchange information in a so-called “bridging” link (Lubell et al., 2014; Reagans and Zuckerman, 2008; Tagliaventi et al., 2010). Matous and Todo (2018) found that interventions linking farmers from farmer groups in different locations helped them access useful external information, and that these farmers became popular as information providers when they returned to their community.

In summary, our case study in coastal Bangladesh indicates that a mixed strategy of targeting influenceable dominant sources of information in the Mnet or Wnet, plus broadcasting information into the diffuse but highly connected Fnet when no dominant sources exist, has the potential to effectively and rapidly disseminate weather and market advice. These actions are likely to reach a maximum number of farmers, including those who are most isolated, lack access to ICTs, and may be underserved by extension services.

### *Access to information, selling price and yields*

Within the full network of our study area, we found no clear relationship between access to market information and mung bean selling price, or between access to weather information and mung bean yields on an aggregated network level. In the Fnet however, we found that citing more friends was significantly correlated to higher yields (Fig. 11). In general, this finding is in line with literature that suggests that farmers with many friends are more likely to receive information on weather forecasts, and may thus have better opportunities to prepare for climate extremes and therefore have higher yields (Borgatti et al., 2018; Doblas-Reyes et al., 2003; Jones et al., 2000). Further, our finding that the farmers’ friendship interaction is significantly correlated to farmers’ access to market information supports our hypothesis that the Fnet could be used as a proxy for market information dissemination (Fig. 11).

The lack of observed relationship between access to weather information and yield could be due to the moderate weather the year this study was conducted, which may have led to little difference in management between farmers with and without access to weather information. The lack of relationship between mung bean selling price and access to market information could be explained by the limited alternative options for selling mung beans in remote locations with low numbers of farm gate purchasers and traders. Consequently, while market information may be of interest, it could be difficult for farmers to act on in negotiation with purchasers, supporting literature that practical constraints may be more important than a lack of market information in smallholder farming systems (Haythornthwaite, 1996; Oliveira and Chana, 2019). On the other hand, literature suggests that isolated farmers may experience substantial benefits in yields and selling prices when they do receive novel weather and market information (Aral et al., 2007). Other factors also influence access to information and yields and prices, namely demography, human capital, total communication volume, individual capacity to seek information and temporal shocks to the flow of information (Aral et al., 2007; Reagans and Zuckerman, 2001)

Our correlation analysis revealed a number of potentially confounding factors. Firstly, farmers with higher gross income and more mung bean area indicated a significantly higher access to weather and market information. Secondly, as distance to the closest market increased, access to weather and market information decreased. These other influential factors could potentially mask the effect of social networks on farmer yield and selling price. On the other hand, the Fnet showed the opposite trend from the information networks, implying that the poorer and more remote farmers are, the more they rely on the friendship network.

### *Limitations of this study*

We applied an ego-network approach because the study area in coastal Bangladesh did not have defined network boundaries. The lack of clear boundaries limited the use of SNA-metrics based on geodesic distances for further assessing the speed of information flow (Borgatti et al., 2018). When considering the speed of information flow, we did not investigate flow over time as the study was only a snapshot in time. Therefore, our speed metric takes connectivity and density as proxies for the potential speed of information dissemination. Additionally, since network density is linked to network size, caution should be used in generalizing our findings as we considered three different networks with different sizes (Borgatti et al., 2018; Hanneman and Riddle, 2014).

Qualitative interviews of the most central actors observed in our networks could have provided useful additional information. In particular, interviews with the most top-cited brokers and input dealers could assist in contextualizing their influential network position.

## Conclusion

Our aim was to identify potential opportunities for improving weather and market advisory dissemination to rural communities and remote and underserved farmers in developing countries. Social Network Analysis was applied as a tool to improve weather and market information dissemination in mung bean farmer communities of coastal Bangladesh. Our study highlights that SNA can be used to reveal hidden structures of information flows in farmer communities by examining farmers' access to information, dominant sources of information, and the potential speed of information flow in a network. Our analysis indicates that information networks differ in structure geographically and that location-specific dissemination strategies are needed. Depending on the local structure of the Wnet or Mnet, it may be possible to identify and utilize dominant actors as entry points to efficiently reach a maximum number of farmers. However, if there are no key actors, or if the aim is to target the most isolated and underserved farmers, broadcasting information in the Fnet would be the better strategy. By applying SNA in this novel way, this research contributes to the development of new methodological applications in the context of agricultural climate services and climate change adaptation research.

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## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix

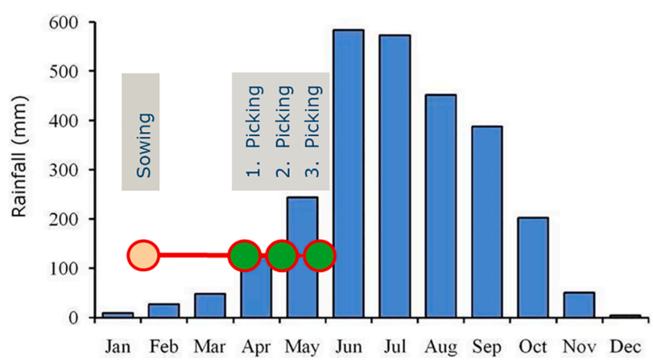


**Fig. A.1.** Climate diagram with rainfall and management steps of mung bean production in southern Bangladesh (modified from Bangladesh Meteorological Department (BMD)).

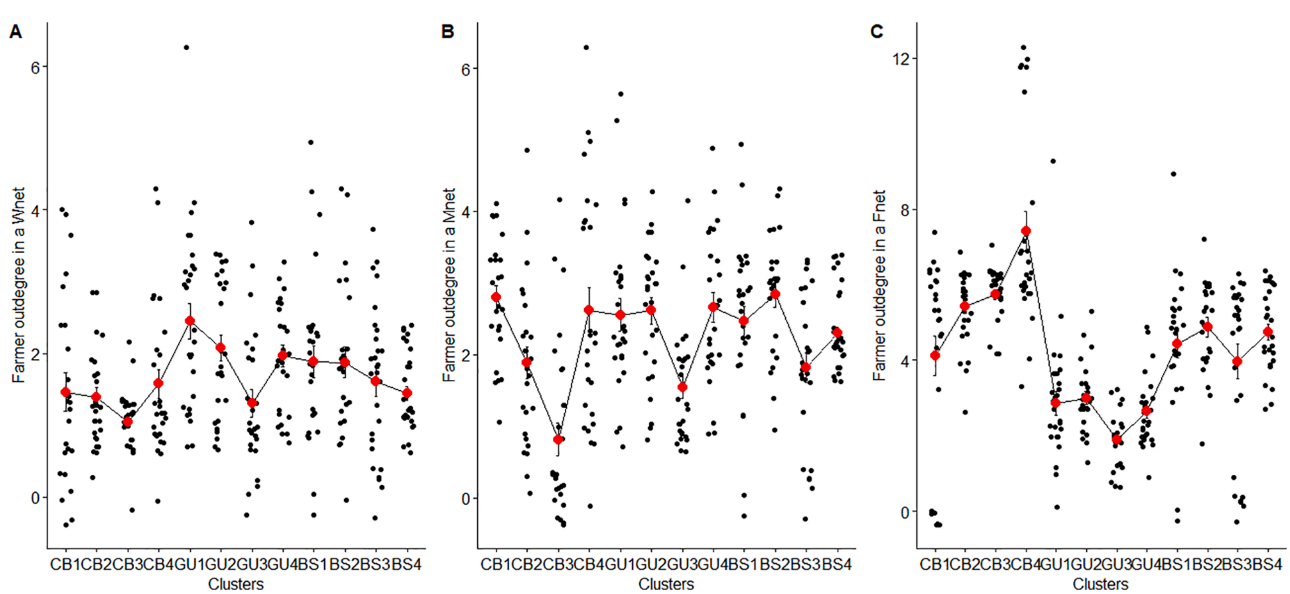


**Fig. B.1.** Farmer's outdegree of the three networks Wnet, Mnet and Fnet on the y-axis different and clusters on the x-axis. The black dots indicate the farmers' individual outdegree per cluster (jittered) while the red dot indicates the average per cluster and network.

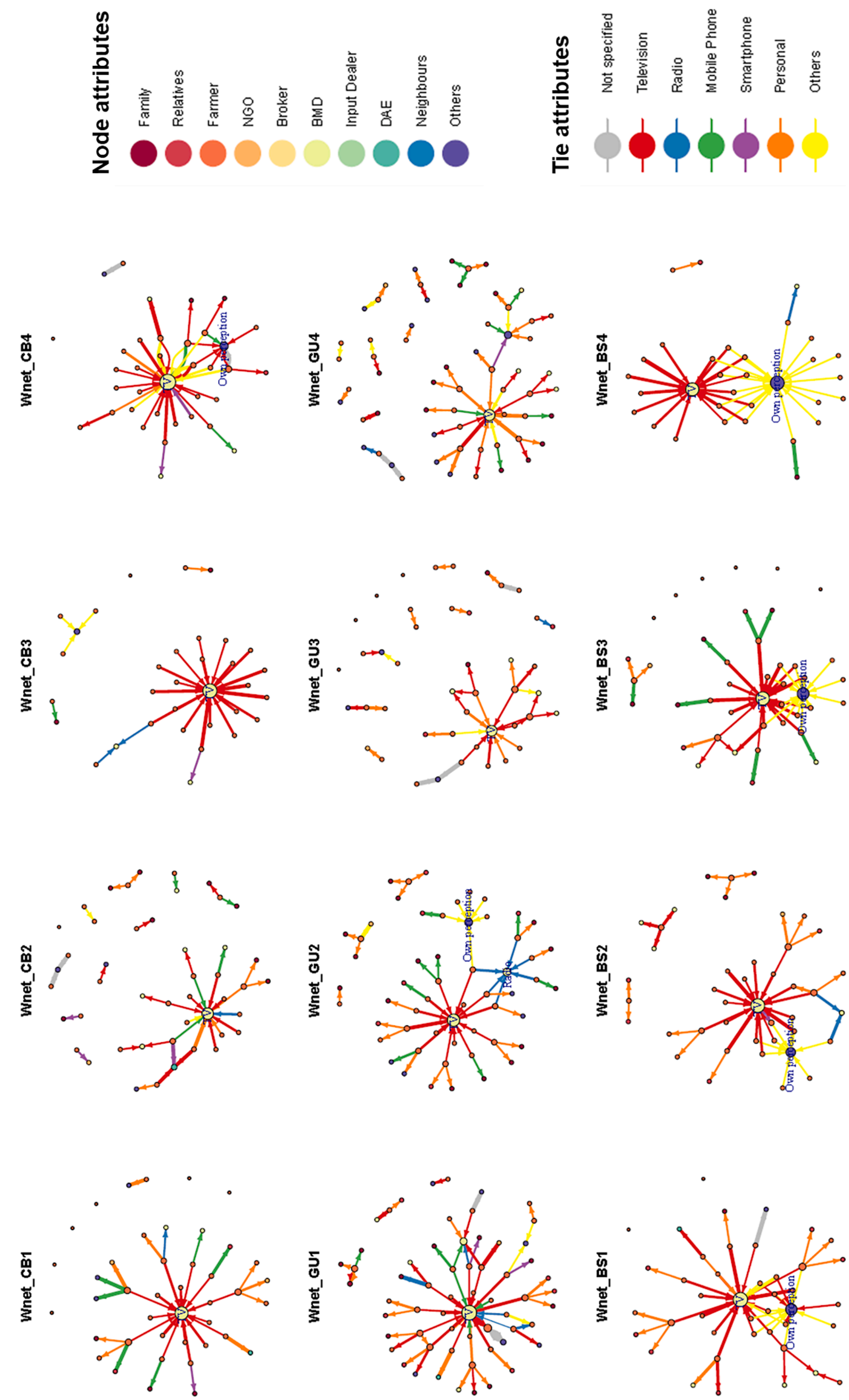


**Fig. C.1.** Farmer's outdegree of the three networks Wnet, Mnet and Fnet on the y-axis different and clusters on the x-axis. The black dots indicate the farmers' individual outdegree per cluster (jittered) while the red dot indicates the average per cluster and network.

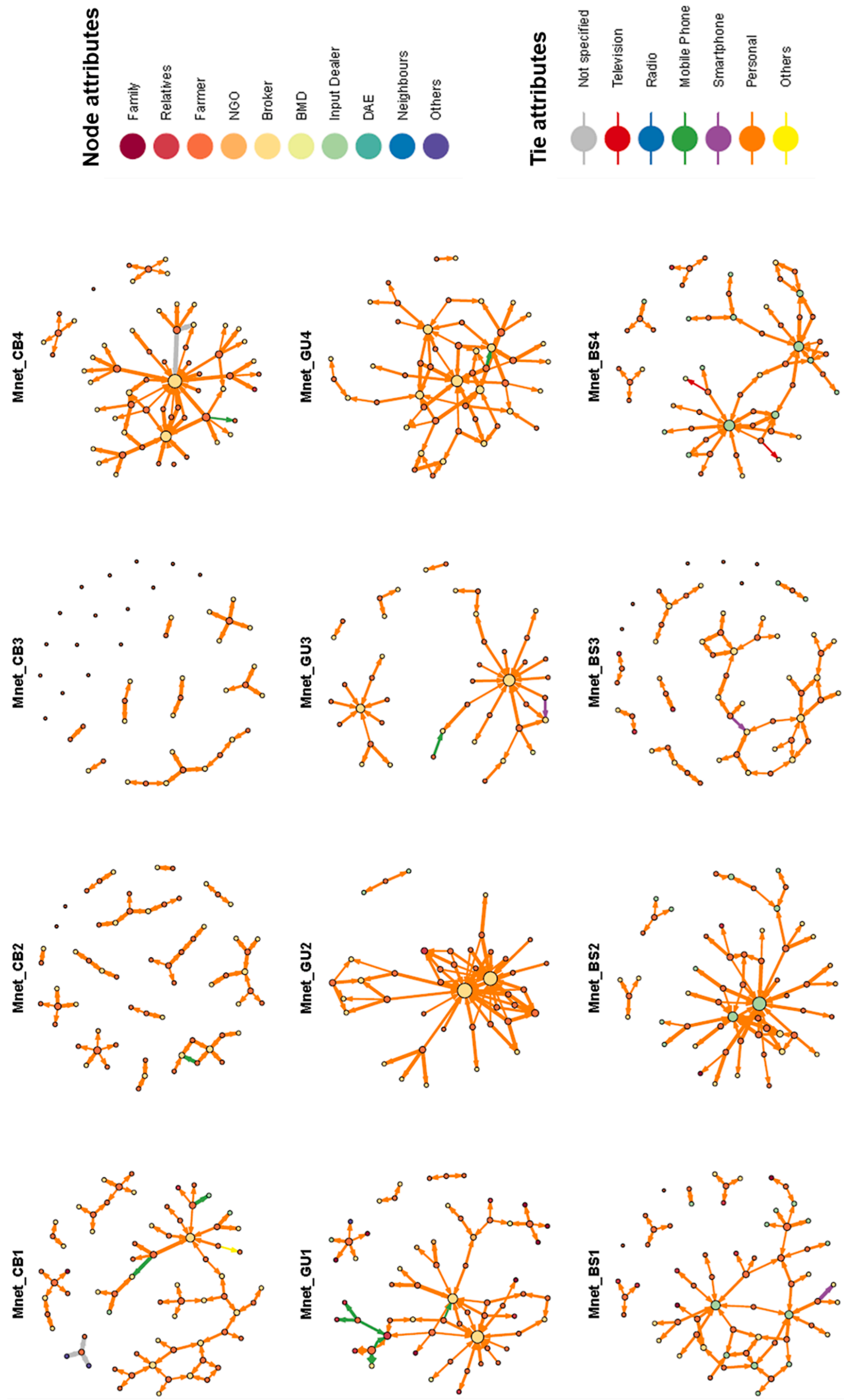


**Fig. C.2.** Weather Information Network Graphs on cluster level.

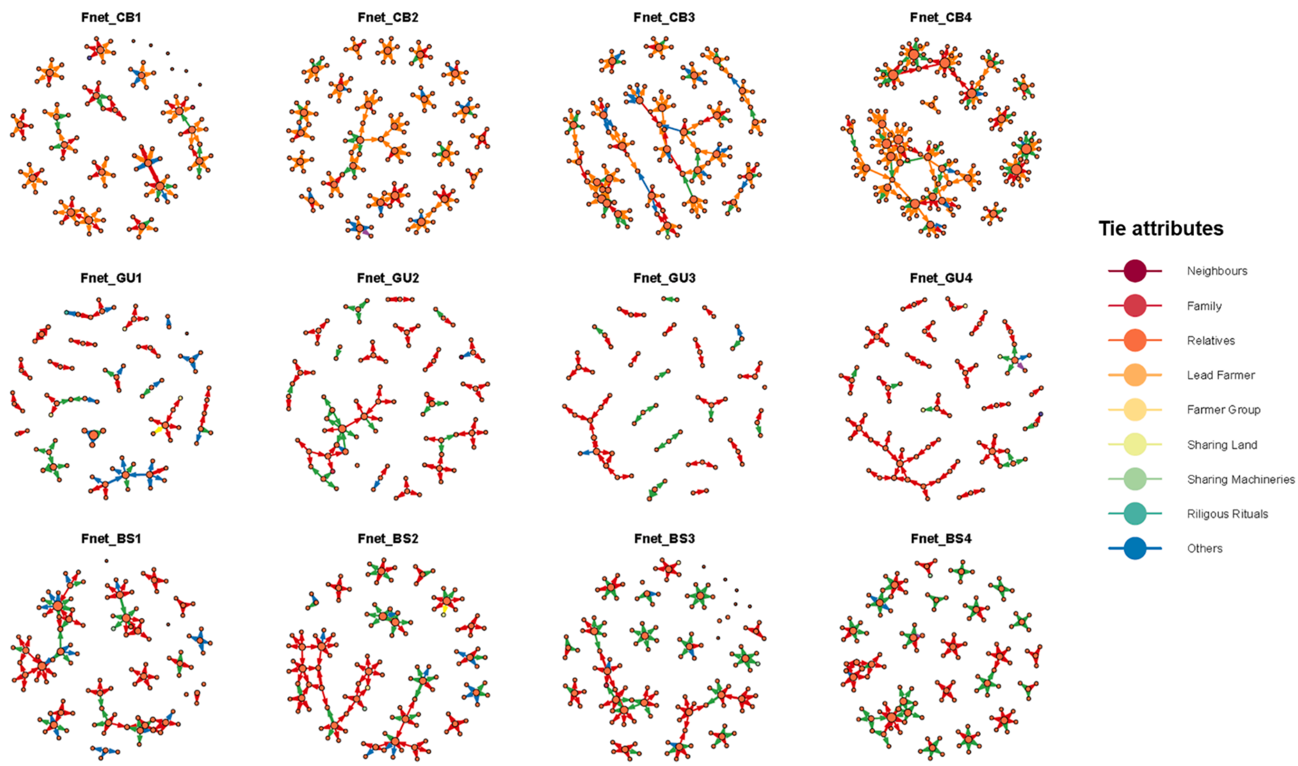


**Fig. C.3.** Weather Information Network Graphs on cluster level.

**Table A.1**
The three cropping seasons of southern Bangladesh (Rawson, 2011).

| Season | Period | Condition |
|---|---|---|
| Kharif-1 | March–May | Pre-monsoon–increasing rainfall |
| Kharif-2 | June–October | Monsoon–heavy rainfall |
| Rabi | November–February | Dry season–occasional rainfall |

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