The Importance of proximity dimensions in agricultural knowledge and innovation systems
Kabirigi, Michel; Abbasiharofteh, Milad; Sun, Zhanli; Hermans, Frans

Published in:
Agricultural Systems

DOI:
10.1016/j.agsy.2022.103465

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2022

Link to publication in University of Groningen/UMCG research database

Citation for published version (APA):

Copyright
Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the “Taverne” license. More information can be found on the University of Groningen website: https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment.

Take-down policy
If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from the University of Groningen/UMCG research database (Pure): http://www.rug.nl/research/portal. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.
The importance of proximity dimensions in agricultural knowledge and innovation systems: The case of banana disease management in Rwanda

Michel Kabirigi\textsuperscript{a, b, *}, Milad Abbasiharofteh\textsuperscript{c}, Zhanli Sun\textsuperscript{a}, Frans Hermans\textsuperscript{a}

\textsuperscript{a} Leibniz Institute of Agricultural Development in Transition Economies (IAMO), Theodor-Lieser-Str. 2, 06120 Halle (Saale), Germany  
\textsuperscript{b} Rwanda Agriculture and Animal Resources Development Board (RAB), Research Department, P.O. Box 5016, Kigali, Rwanda  
\textsuperscript{c} Faculty of Spatial Sciences, University of Groningen, Landleven 1, 9747 AD, Groningen, the Netherlands

\textbf{HIGHLIGHTS}

- Different forms of proximity are important to be incorporated into AKIS research.
- Geographical proximity plays a role in the informal networks of larger villages.
- Cognitive and social forms of proximity take over where distance is not important.
- Geographical distance doesn't affect the official government extension system.
- Farmers are socially close in a smaller community where distance does not matter.

\textbf{ARTICLE INFO}

Editor: Laurens Klerkx  
Keywords: Knowledge exchange network, Proximity dimensions, BXW, Social network analysis, Resilient agro-ecosystems

\textbf{ABSTRACT}

\textbf{CONTEXT:} Social networks play an important role in the diffusion of knowledge, and farmers draw on their personal networks to enhance their adaptive capacity to shocks. Different forms of proximity have been long recognized as important factors in knowledge and information exchanges. However, the specific roles and their interactions in agricultural knowledge and innovation systems (AKISs) are still far from clear. In this study, we investigate the underlying forces that drive tie formation within the knowledge-sharing networks of banana farmers in four different villages in Rwanda.  

\textbf{OBJECTIVE:} Our study has three objectives: First, we discuss the importance of various types of proximities in AKIS research. Second, we empirically contribute to how different forms of proximity influence the way knowledge diffuses in formal and informal networks by studying a plant disease's management. Finally, we discuss our findings' relevance for targeted interventions to help rural communities transition to greater resilience.  

\textbf{METHODS:} We review different proximity concepts and adapt them for use within an AKIS context. We then apply this framework to assess the proximity effects on the advice-seeking networks of banana farmers in four purposefully chosen villages in Rwanda. We used a structured questionnaire to collect social network information about the management of banana Xanthomonas wilt (BXW), from all banana growers ($N = 491$) in these four villages. We distinguished the informal advice networks among farmers from the official government extension networks using ERGMs.

\* Corresponding author at: Leibniz Institute of Agricultural Development in Transition Economies (IAMO), Theodor-Lieser-Str. 2, 06120 Halle (Saale), Germany.  
E-mail address: kabirigi@iamo.de (M. Kabirigi).

https://doi.org/10.1016/j.agsy.2022.103465

Received 1 August 2021; Received in revised form 14 July 2022; Accepted 15 July 2022  
Available online 9 August 2022  
0308-521X/© 2022 Elsevier Ltd. All rights reserved.
1. Introduction

The agricultural knowledge and innovation system (AKIS) framework has become a popular analytical framework to study how agricultural knowledge is co-produced and disseminated. AKIS describes how actors, networks, and institutional environments play a significant role in these processes (Abebe et al., 2013; Rivera et al., 2005; Spielman et al., 2009). This approach has broadened the previously linear view of agricultural innovation processes to a distributed process in which different actors can play roles to solve the so-called “wicked” (complex) problems associated with unsustainable technologies and practices (Hobinck et al., 2021; Hermans et al., 2015; Luweiss and Aarts, 2011). With the rising interest in collaborative processes, collaborative networks have become a popular object of study. Within the last decade, the AKIS literature has adopted a network perspective that highlights the role of knowledge/advice networks to explain and predict information flows and their role in enhancing smallholders’ capacity to innovate (Campagnone and Hellec, 2015; Danielsen et al., 2020; Hermans et al., 2017b; Rudnick et al., 2019; Spielman et al., 2011).

In addition, the literature has shown a positive association between knowledge networks and agricultural systems’ resilience (Darnhofer et al., 2016; Sumane et al., 2018; Tuttonell, 2020). The need for resilient agricultural systems increases constantly insofar as agriculture is exposed to multiple shocks, stresses, and growing uncertainty (Meuwissen et al., 2019). Such networks facilitate knowledge exchange including information relevant to coping with the multiple shocks, stresses, and growing uncertainty farmers are exposed to (Meuwissen et al., 2019). Dense social networks are therefore both the expression of and prerequisite for developing different types of social capital and trust (Aguilar-Gallegos et al., 2015; Cofre-Bravo et al., 2019).

Although this network perspective has been successfully applied to studying the effects of different network characteristics at the macro level, not a lot of attention has been paid to the underlying forces that drive tie formation within such networks. We aimed to address this gap by investigating what types of proximity influence the formation of knowledge-sharing ties in a formal and an informal advice network. Proximity refers to the individual’s tendency to form interpersonal relationships with those who are close by. However, closeness is viewed in the literature as a multidimensional concept that is not limited only to geographic distance (Boschma, 2005; Geldes et al., 2015; Mattes, 2012).

This paper is structured as follows: The subsequent Theoretical Background section digs deeper into the proximity literature and how these insights can be applied to agricultural advice networks in AKIS. We discuss how different forms of proximity influence the diffusion of knowledge, especially geographical proximity. A geographical distance does not prohibit collaboration and learning; on the other hand, being far away does not guarantee collaboration and learning; on the other hand, being far away does not prohibit them, either. Besides geographical proximity, four other forms of proximity have been distinguished: i) cognitive proximity, ii) social proximity, iii) institutional proximity, and iv) organizational proximity. Geographical and non-geographical proximities tend to be positively correlated, which explains why the effect of geographical proximity is overestimated if other forms of proximity are not controlled for (Balland et al., 2020). At the moment, there is an ongoing debate in the scientific literature about whether these different forms of proximity can complement or substitute for each other—for instance, whether one type of proximity can compensate for the lack of another. Recently, the extant literature on economic complexity suggests that the complexity of the knowledge exchanged determines whether proximity dimensions complement or substitute for one another (Balland et al., 2022). In the following section, we elaborate on the five forms of proximity and their relevance in AKIS functioning research.

Geographical proximity refers to the spatial or functional distance between actors. It can be measured with different indicators: absolute geographical distance, travel times, perceived distance, or co-location in...
the same geographical unit. Geographical proximity is thought to be especially significant for the exchange of tacit knowledge (Gallaud and Torre, 2005; Rallet and Torre, 1999). Tacit knowledge is non-codified, disembodied knowhow that is acquired via the informal take-up of learned behavior and procedures (Howells, 1996). Formulated slightly differently, tacit knowledge is the knowledge, skills, and abilities that are gained through experience and are often difficult to put into words or otherwise communicate. Face-to-face interactions, demonstrations, and learning by doing are the best ways to share such knowledge; the further actors are located from each other, the more difficult this exchange becomes. Within an AKIS context, geographical proximity is therefore important in situations where access is important or tacit knowledge is exchanged. As agriculture is a geographically localized phenomenon, much knowledge about important local conditions with regard to climate, soil, and water is stored as tacit knowledge by farmers (Mwongera et al., 2017). Temporary geographical proximity is another form of geographical proximity that considers the possibility of being geographically closer for a certain period of time by traveling to different locations, satisfying the need for face-to-face contact between actors (Rallet and Torre, 2009).

Cognitive proximity is commonly defined as the similarities in the ways actors perceive, interpret, understand, and evaluate the world (Knoeben and Oerlemans, 2006). Some authors speak in this regard about the “logic of similarity” when actors share common knowledge, or cultural or religious values (Pachoud et al., 2020; Pachoud et al., 2019; Polge and Torre, 2018; Torre et al., 2019a). It has been shown that cognitive proximity can both enable and constrain learning. While cognitive diversity increases creativity and the scope of learning, too much cognitive diversity makes it difficult to reach consensus (Nootboom et al., 2007). That is to say, as cognitive proximity increases, the benefit of a given relation decreases (Balland et al., 2022). Within an AKIS context, cognitive distance can be related to these differences between worldviews (for instance, between farmers and non-farmers). This can lead to a fragmentation of visions on the countryside (Hermans et al., 2009; Vermunt et al., 2022). There might also be large cognitive distances between different types of farmers within the agricultural sector itself due to increasing specialization and the application of new high-tech innovations (Klerkx and Rose, 2020).

Social proximity has been used in two different ways that result from different operationalization of the concept of actors’ embeddedness in other social ties. In the first meaning of social proximity, the concept refers to conditions that facilitate the creation of trust. Such conditions can be formed by prior social relationships such as friendship, kinship, or experiences in earlier collaborations. The notion of social proximity stems from personal ties among members of different organizations, which enhance trust and effective communication. This definition is featured prominently by Uzzi (1997).

The second way the term “social proximity” has been used takes the embeddedness of the actor’s position within a network as a basis. Actors with the same type of network position (sometimes also referred to as structural equivalence) are considered to be socially proximate. When actors share the same types of network position—for instance, with regard to their connectivity or degree of centrality—they develop the same types of attitudes or behavior due to environmental shaping (Borgatti and Foster, 2003), which in turn might make it easier for them to develop a tie in the network.

Thus, social proximity within AKISs can either deal with embeddedness (defined as relations of trust) or network position. As agriculture is often a family business, relationships and trust are also developed over generations. At the same time, certain farmers’ positions within the network may have also shaped their behavior and attitudes. This can apply to opinion leaders, who occupy the intermediary position between the formal and informal AKISs.

Institutional proximity refers to North (1990), who stated that institutions act as “the formal and informal rules of the game.” Differences in institutional context often relate to the formal institutions that govern different geographical contexts (countries), but also different industrial sectors and their safety and quality standards. Institutional proximity within an AKIS can thus relate to differences in intellectual property rights, but also to food safety rules, which are enforced over the entire value chain and make it difficult for small-scale food producers to participate (Ramirez et al., 2018).

Organizational proximity is about the ‘logic of belonging to the same organization and about various modes of conflict resolution, for instance through the mobilization of hierarchical control in multinational corporations of their subsidiaries (Balland et al., 2020; Rallet and Torre, 1999). Organizational proximity would therefore be well captured in AKIS by the membership of farmer cooperatives, especially if that membership implies that farmers share similar working routines. With the rise of ‘agro-holdings’ that incorporate different entities within the same holding (Hermans et al., 2017a) this type of hierarchical control that signifies close organizational proximity could be relevant for inclusion within AKISs as well.

Table 1 provides an overview of the different forms of proximity and their relevance to AKIS research. A couple of remarks must be made here. First of all, proximities are not static, but dynamic. Research into the co-evolution of different forms of proximities and network structures has shown that different types of proximities may rise to prominence over time (Abbasiharofteh and Broekel, 2020; Ballard, 2012; Ter Wal, 2013). The second issue to be aware of is that proximities can act both positively and negatively on innovation processes. This has been described as the “proximity paradox” (Boschma and Frenken, 2010; Broekel and Boschma, 2012): too little proximity may hinder innovative performance, but too-close proximity may be a problem as well.

In this regard, the proximity concept shows some similarities with

| Table 1 Forms of proximity, their meaning in social networks, and applicability to AKIS. |
|----------------------------------|-----------------|-------------------|------------------|
| Form of proximity                | Key dimension   | Definition                     | Measures                      |
| Geographical proximity          | Distance        | Geographical and functional distance between actors | The opposite of distance (physical and/or functional), travel distance |
| Cognitive proximity             | Knowledge gaps or overlaps | Shared knowledge, references, and interpretative schemes | Type/field of innovation, source of knowledge, level of understanding, technology used, labor mobility |
| Social proximity                | 1) Trust based on social relations | 1) Shared social context and common past | 1) Social embeddedness in one’s ethnic group, kinship, friendship |
|                                  | 2) Structural equivalence | 2) Same type of network position | 2) Same number of ties, bridging ties, the inverse of geodesic distance |
| Institutional proximity         | Trust based on common institutions | Shared formal rules and regulations | Same organizational type, or functioning under the same operating standards (quality or safety standards) |
| Organizational proximity        | Control and power | Shared organizational structures, routines, and rewards that facilitate collaboration and conflict resolution | Membership in same organization, business board, subsidiaries, or parent company |

Source: adapted from Boschma (2005).
another theoretical concept that has become popular alongside the rise of network science—that of social capital. Similar to the notion of proximity, when social capital is viewed through a lens of social network analysis, the types of links and the structure of a network become relevant characteristics. Like proximity, social capital is a multidimensional concept that actually contains several different concepts. For instance, some authors distinguish between bonding, bridging, and linking social capital among farmers and between farmers and agricultural extensionists (Cofre-Bravo et al., 2019; Klerkx and Proctor, 2013, p. 16). Bonding social capital, based on Putnam (1993), indicates the presence of cooperative relationships between members of a network who are similar in a sociodemographic sense, resulting in dense multiple networks with strong ties and high trust. This form of social capital thus refers to the same type of embeddedness that the first notion of social proximity refers to. Bridging social capital, as described by Burt (1992, 2005), can be seen as the second form of social proximity when it is defined as the structural equivalence of actors who are located near a “structural hole.” The term structural hole denotes a gap between two neighbouring actors who are not directly connected in a social network (Burt, 2004). Finally, linking social capital is trusting relationships between people who interact across explicit, formal, or institutionalized power gradients. Within the proximity framework, this is captured by the concept of organizational proximity.

In the remainder of this paper, we investigate some of these proximity dimensions as they played out in the context of the knowledge-sharing networks on BXW in four different Rwandan villages. We use different proximity categories as the driving forces of tie formation with the formal and informal knowledge-sharing networks.

2.2. Description of Rwandan AKIS

In Rwanda, agricultural knowledge is channeled through both a formal government-led extension service, but also by more informal farmer-to-farmer knowledge exchange approaches. The formal extension services are coordinated by the Rwanda Agriculture and Animal Resources Development Board (RAB) under the Ministry of Agriculture (MINAGRI) (MacNairn and Davis, 2018). The formal national extension structures and staff extend down to the sectoral level. On the other hand, the RAB has established a farmer-facilitated extension model, the Twigire Muhinzi, to deploy staff from the national to the village level (Silvestri et al., 2019). The Twigire Muhinzi is a farmer-to-farmer extension model, referred to as a community-based extension system, that uses farmer field schools (FFSs) and farmer promoters (FPs). In the first instance, a group of farmers are mobilized around a field school; while in the second case, an FPs organizes farmers (a “Twigire group”) around a demo plot. FFS facilitators and FPs are recruited from among local farmers and equipped with different levels of training by the RAB. At the time of our investigation, information and communications technology tools such as basic mobile phones and smartphones were not used to reach farmers.

2.3. Hypotheses

Based on the background literature, we can develop a number of hypotheses regarding how different forms of proximity will play out in formal and informal extension networks. However, we did not test all five proximities. For now, we limit our discussion to the three types of proximity most appropriate for our study: geographical, cognitive, and social. We consider geographical proximity because it has been shown to be a critical factor that triggers knowledge exchange in numerous case studies: it causes random encounters, trust-building, and interactive and non-interactive learning (Boschma, 2005; Glückler, 2013). We also investigate the role of cognitive proximity because this takes into consideration the extent to which farmers’ mental maps overlap (Nooteboom, 2000). Mental maps are formed and influenced by farmers’ fields of work, and in our case study, whether they are affected by BXW. Finally, we claim that social proximity is critically important with arguably high degrees of trust and social cohesion. In such a network, homophily among farmers and embeddedness in the local social network (used to define social proximity variables) gain importance over status in creating and absorbing knowledge relations (Lazega et al., 2012). It is important to note that we refrained from investigating organizational and institutional proximities, as these factors are investigated more often in inter-organizational relations that cross-regional and national boundaries.

Our hypotheses regarding geographical proximity are derived from the accessibility argument. The farther away two actors are, the less likely they will develop a knowledge-sharing bond. This argument is applicable for informal and formal advice networks. Thus:

- **H1a.** The farther away two actors are, the less likely they will share an advice tie in the informal network.
- **H1b.** The farther away a farmer is located vis-à-vis the location of the extension office, the less likely he or she is to be visited by an extension worker.

Regarding cognitive proximity, it is important to know that there are three types of banana farmers in Rwanda. Kabirigi et al. (2022) identified three banana farm types based on total land area, the proportion of land allocated to cooking or beer banana production, and the proportion of cooking or beer bananas sold and consumed. Farm types are i) cooking banana farms, ii) beer banana farms, and iii) mixed farms. In this regard, we hypothesize that a shared specialized production system leads to cognitive proximity.

- **H2a.** Farmers who belong to the same type of banana farms should be cognitively close, and therefore should have a greater chance to share advisory ties in the informal network.

An alternative and somewhat competing hypothesis may also be formulated for cognitive proximity. When farmers have had experience dealing with the disease, other farmers might seek them out for advice. This would indicate low or even negative cognitive proximity and a case in which opposites attract.

- **H2b.** Farmers with BXW infections in their banana fields are more likely to seek advice from other farmers who have already experienced BXW.

We used both definitions of social proximity (see Table 1). First, we noted social proximity with regard to actors’ embeddedness in their network. This is a node-level variable, measured for each actor as the inverse of the number of indirect relations at distance 2. This is worth noting that although theoretically social proximity is defined at the dyad level, this node level variable has been empirically used in several studies to operationalize social proximity (Hermans, 2021). The number of distance 2 connections creates an indirect relations effect. It is defined as the number of actors to whom an actor is indirectly tied through one intermediary (i.e., at geodesic distance 2). If this number is high, the intermediary has a lot of connections and the node is a diverse source of information, albeit indirectly. A higher number indicates the node could be part of a dense local cluster. If the number of distance 2 connections is low, the node might be at the periphery of the network. The inverse is used to bring the index into a range between 0 and 1. Applied to our farmer network, we thus hypothesize that:

- **H3a:** Farmers that are socially close as measured by the inverse of geodesic distance 2 are more likely to exchange information.

For the second definition of social proximity, we examined the embeddedness of actors with regard to other social ties. Here, we looked at actors’ ages. We assumed that within the context of Rwandan villages,
age groups would tend to seek interaction among themselves. In Rwanda, people are culturally stratified according to age, where older people occupy a higher social status (Sabates-Wheeler et al., 2020). Furthermore, younger people might have developed prior ties in schools or other social activities, while older persons might have developed ties over previous years living in the village. Thus, we hypothesize that

- **H3b**: Farmers who belong to the same age group (same generation) are more likely to exchange information.

In the remainder of the paper, we test our hypotheses.

3. Data and methods

3.1. Study area and respondents

We conducted a survey in two districts, the Kayonza District in Rwanda’s Eastern Province and Burera District in the Northern Province. Both districts produce bananas, but they differ in terms of climate, soil, and banana production systems (see Fig. 1). In each district, we selected two villages based on their geographical distance to extension services: one village located far from the district extension office (less accessible) and one near (more accessible). We used cost–distance analysis in ArcGIS to identify the least costly path to reach each village, taking into account all physical barriers influencing villages’ accessibility.

Table 2 summarizes the demography and BXW history in each study village. In all villages, it took one year after the first banana field was affected by BXW to reach peak incidence rates (>80% of the village affected), except in Murambo village, where it took around 5 years.

To collect the data for our network studies, we attempted to reach all the individuals involved in the network. To collect geographical locations, we visited farmers in their homes. Table 3 shows that we had a very high response rate (> 85%) sufficient for reliable network analysis (Grosser et al., 2010). In addition, the table shows some of the other socioeconomic data we gathered to operationalize the different forms of proximity by education level, gender, age categories, and types of bananas grown on each farm: beer bananas or cooking bananas.

3.2. Data collection

A team of researchers trained by the primary author conducted a survey from November 2018 to January 2019. Social network data consisted of responses to two main questions: i) From whom have you received advice regarding BXW management? and ii) To whom have you provided advice regarding BXW management? Respondents were encouraged to name as many contacts as they could remember. The names were then categorized into different types: fellow farmers, extension officers, and local administrators. The questionnaire was developed in the Open Data Kit format, which allowed us to use mobile devices to record information. This tool also used GPS devices to collect houses’ latitude, longitude, and altitude values in our case. Before analysis, data were subjected to cleaning, mainly to harmonize the spelling of names. Data were then split to construct an informal farmer advice network and a formal extension network. It is important to note that the formal extension network we constructed depended solely on the data provided by the farmers. We did not check these data with the different types of extension workers (district agronomists, RAB, etc.) themselves.

3.3. Proximity variables

We calculated geographical proximities among households based on
connecting the two nodes in a given social network. In the context of our proximity literature, greater geodesic distance, they are less socially proximate (i.e., have a work, this implies that if two farmers are socially distant (i.e., display variable for our exponential random-graph model (ERGM). It is important to mention that the term “geodesic distance” has different definitions in geometry and network literature. We use this term in the context of network science to mean the number of edges of the shortest path connecting the two nodes in a given social network. In the context of our work, this implies that if two farmers are socially distant (i.e., display greater geodesic distance), they are less socially proximate (i.e., have a lesser inverse of geodesic distance). This method is common practice in proximity literature.

We measured social proximity measured for each actor as the inverse of the number of indirect relations at distance 2. We used this node-level variable for our exponential random-graph model (ERGM). It is important to mention that the term “geodesic distance” has different definitions in geometry and network literature. We use this term in the context of network science to mean the number of edges of the shortest path connecting the two nodes in a given social network. In the context of our work, this implies that if two farmers are socially distant (i.e., display greater geodesic distance), they are less socially proximate (i.e., have a lesser inverse of geodesic distance). This method is common practice in proximity literature.

We used age categories as another variable to measure social proximity, assuming that farmers who belong to the same age category are more likely to interconnect. McPherson et al. (2001) determined that age homophily is one of the strongest forces of social tie formation. In the same vein, sociologists found age similarity to be a strong predictor of friendship tie formations and of exchanging information on work, sociability, and neighborhood support (Feld and Grofman, 2009; Fischer et al., 1977; Verbrugge, 1977). Marsden (1988) also showed that if two persons are further apart in age, it is less likely that they “discussed important matters.” Belonging to the same age group is the variable that best depicts a measure of social proximity, shared social context, and common past among farmers, particularly in areas such as rural Rwanda where there is no social mobility.

3.4. Exponential random-graph model description

We applied an ERGM to test our propositions regarding the influence of the proximity dimension in the informal network. The main reason that we selected ERGMs over traditional econometric models is that the former accounts for the structure of interactions in the knowledge/advice network. More specifically, ERGMs allow to create and include variables that approximate the endogenous effect of relational forces (e.g., the position of farmers in a clique). In other words, this feature of ERGMs enables us to control for dependencies among farmers in forming advice-seeking relations. ERGMs are so-called statistical inference models (Snijders, 2011). These models take the observed network as the dependent variable, then develop and test hypotheses about the social processes that might have led to its creation and development. It goes beyond this manuscript to fully introduce these types of models, but good introductory texts can be found in Lubell et al. (2012); Robins et al. (2007), and Harris (2014).

3.5. ERGM settings and proximity operationalization

We analyzed social network information using R (Version 4.0.3), mainly the statnet, ergm, and ggplot2 packages. Terms were added in consecutive blocks to examine their relative contribution to enhancing the models’ goodness of fit (Goodreau, 2007) (see Table 6 in Appendix). For each village, we evaluated four models. We started with a simple random graph model (M0) that only included a term for edges and in which all nodes had an equal chance to form a tie. In subsequent steps, we introduced greater complexity by adding terms corresponding to our hypotheses. First, we introduced the proximity effects (M1) using the nodematch R term. Social proximity calculated as geodesic distance 2 was operationalized using the nodematch R term, which is suitable for node-level continuous variables. Social proximity based on age, cognitive proximity based on farm type, and cognitive proximity based on experience with BXW were added as homophily tests using the nodematch R term. In addition to M0 and M1, we added M2 the individual-level control variables which are education level and gender using the nodefactor R term. In addition to M0, M1, and M2, for our full model, we tested for nodes with high outdegrees to create ties (gwodegree), and geometrically weighted edgewise shared partnerships (gweesp and gdwsp) as control variables at the network level. Note that we used gweesp, gwsp, and gdwsp mainly as control variables to avoid model degeneration, and we did not interpret them theoretically. In this empirical setting Edges (approximating the density of networks), preferential attachment (gwodegree), cohesion effect (gweesp), and multi-connectivity effect (gdwsp) are variables approximating endogenous effects. On the other hand, individual-level controls (education and gender) and social proximity based on geodesic distance are node level variables; and geographical, cognitive, and age-related social

Table 2
Study villages’ demography and BXW history.

<table>
<thead>
<tr>
<th>Village</th>
<th>Households</th>
<th>Banana farmers</th>
<th>First BXW observation</th>
<th>Peak incidence year</th>
<th>Peak infection (% of village area)</th>
<th>Distance to extension office</th>
</tr>
</thead>
<tbody>
<tr>
<td>Murambo</td>
<td>118</td>
<td>112</td>
<td>2009</td>
<td>2014</td>
<td>85</td>
<td>Near</td>
</tr>
<tr>
<td>Karambo</td>
<td>97</td>
<td>97</td>
<td>2011</td>
<td>2012</td>
<td>95</td>
<td>Far</td>
</tr>
<tr>
<td>Rusera</td>
<td>223</td>
<td>218</td>
<td>2015</td>
<td>2016</td>
<td>80</td>
<td>Near</td>
</tr>
<tr>
<td>Rubira</td>
<td>126</td>
<td>93</td>
<td>2016</td>
<td>2017</td>
<td>80</td>
<td>Far</td>
</tr>
</tbody>
</table>

Table 3
Characteristics of respondents in study villages.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Category</th>
<th>Karambo (n = 87)</th>
<th>Murambo (n = 96)</th>
<th>Rubira (n = 91)</th>
<th>Rusera (n = 214)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Response rate (%)</td>
<td>None</td>
<td>86</td>
<td>90</td>
<td>98</td>
<td>98</td>
</tr>
<tr>
<td></td>
<td>Education level (%)</td>
<td>33.3</td>
<td>25.3</td>
<td>35.2</td>
<td>19.6</td>
</tr>
<tr>
<td></td>
<td>Primary</td>
<td>55.2</td>
<td>65.7</td>
<td>56</td>
<td>69.2</td>
</tr>
<tr>
<td></td>
<td>Lower</td>
<td>3.4</td>
<td>4.0</td>
<td>7.7</td>
<td>7.9</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td>8.1</td>
<td>5.0</td>
<td>1.1</td>
<td>3.3</td>
</tr>
<tr>
<td>Gender (%)</td>
<td>Female</td>
<td>41.4</td>
<td>22.2</td>
<td>57.1</td>
<td>59.8</td>
</tr>
<tr>
<td></td>
<td>Male</td>
<td>58.6</td>
<td>77.8</td>
<td>42.9</td>
<td>40.2</td>
</tr>
<tr>
<td>Age category (%)</td>
<td>Young (≤ 25 y)</td>
<td>5.8</td>
<td>8.4</td>
<td>8.5</td>
<td>5.4</td>
</tr>
<tr>
<td></td>
<td>Mid-age (26-50 y)</td>
<td>49.4</td>
<td>46.3</td>
<td>46.6</td>
<td>63.2</td>
</tr>
<tr>
<td></td>
<td>Old (&gt; 50 y)</td>
<td>44.8</td>
<td>45.3</td>
<td>45.3</td>
<td>31.4</td>
</tr>
<tr>
<td>Farm type (%)</td>
<td>Beer</td>
<td>16.1</td>
<td>39.6</td>
<td>4.3</td>
<td>7.6</td>
</tr>
<tr>
<td></td>
<td>bananas</td>
<td>4.6</td>
<td>14.6</td>
<td>4.9</td>
<td>13.6</td>
</tr>
<tr>
<td></td>
<td>Mixed</td>
<td>79.3</td>
<td>45.8</td>
<td>90.8</td>
<td>78.8</td>
</tr>
</tbody>
</table>
proximities are dyad level variables that capture the exogenous effects (Hunter et al., 2008).

AIC and BIC (see appendix) coefficients were the lowest for our final model, suggesting the best fit. Furthermore, to ensure confidence in our ERGM model, we performed a goodness-of-fit test.

In the formal extension network, we mapped relationships between a few extension agents and many farmers. We adopted a more straightforward method by creating a null expectation via rewiring the observed network (Cimini et al., 2019). In doing so, we rewired relations between extension agents and farmers while ensuring that no farmer–farmer ties were included. A null model is a simulation that imitates the functionality of an observed network to generate datasets against which an observed dataset can be compared (Farine, 2017). To do so, we selected random farmers and their geographical locations from our nodelist, then assigned them to the edgelist by creating 100 sets of simulated random relations, keeping the number of ties constant. If the simulated networks differed significantly from the observed empirical network characteristics, this would indicate that the empirical network possessed a non-random quality—in our case, that distance influences tie formation.

4. Results

4.1. Network characteristics

Figs. 2 and 3 depict the four villages’ informal and formal networks. Table 4 shows the main characteristics of these networks. In general, the informal networks were more densely connected than the formal government extension system. The latter also featured a significant number of isolated nodes, indicating farmers who were not being reached through the official extension network. Fig. 2 shows that the informal networks of banana farmers in the study villages were highly centralized around a couple of highly influential nodes. These central nodes consisted of Farmer Promoters (FPs), but also farmers who were part of their

Fig. 2. Farmers seeking BXW management advice from informal social networks within the study villages.
official village administrations. These types of people thus held central brokerage positions that facilitated the flow of information from the formal extension network to the informal network. This structure shows the importance of the Farmer Field School facilitators (FFSs) and FPs in Rwanda’s Twigire Muhinzi extension system.

4.2. Proximity dimensions

Results for our hypothesis testing the relevance of proximity for the formation of network ties are presented in Table 5 (ERGM results) and Fig. 4. We will first present the results for the proximity dimension of the informal advice network. Subsequently, we will discuss the results for the influence of distance on the formal extension network.

4.2.1. Proximity dimension in the informal advice network

Table 5 shows that geographical proximity had a statistically significant and positive effect on the likelihood of creating knowledge exchange ties in the larger villages (in terms of geographical area) of Rusera and Murambo villages, but not in the smaller villages of Rubira and Karambo. Thus our first hypothesis (H1a) that low geographical proximity increases the likelihood of an advice tie to occur, can only be accepted for the largest villages. We speculate that this might indicate the existence of a threshold size after which distance starts to become a factor because this would also explain some of our other findings.

Results show that the tendency to form advice ties by farmers belonging to the same farm typology was again significantly positive in the small Rubira and Karambo villages, but that they were significantly negative for the two large villages. In small villages, it is not such an additional effort to seek out similar types of banana farmers and the positive value indicates a process of homophily in these villages. In the large villages distance starts to play a role and farmers might look for advice from their direct neighbors who are not necessarily the same type of banana farmers.

The probability to connect based on having experienced the BXW was not significant except in Murambo village. Here, the possibility of tie formation was actually positive. This could be explained by the fact that almost all farmers have experienced the disease. The networks are therefore dominated by experienced farmers who ask advice from each other.

The social proximity based on social embeddedness in the network (based on geodesic distance 2) was positively significant in the Rubira and Karambo villages, thus, H3a was accepted in these smaller villages.

Fig. 3. Government-facilitated extension agents’ formal BXW management advisory networks with farmers. Red dots represent official extension entities; yellow dots represent banana farmers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
We, therefore, argue that social proximity was a significant driver of knowledge exchange only in smaller communities. There was a positive and significant tendency to form knowledge exchange ties between farmers belonging to the same age group in all villages except Murambo. Therefore, the H3b was refuted in Murambo village. However, the positively significant effect of social proximity based on age group in the other villages indicates that there is a generational process of homophily present in these villages.

4.2.2. Control variables

We checked the relevance of the control variables at the node level, namely gender, and the education of respondents. We found negative and statistically significant coefficients for all our control variables. This indicates the absence of the formation of ties based on being in the same category. In other words, farmers of the same gender and similar education level are not likely to interact and exchange BXW management knowledge. Using a mixing matrix we found that women play a marginal role in the advice networks, and it seems that they are not asked for advice, not even by other women. Farmers who did not go to school are less likely to create ties for BXW knowledge exchange.

4.2.3. Distance and the formal extension provision to farmers ((H1b)

Results of the null expectation simulation, presented in Fig. 4, show that the distance to the farmer does not predict the visit by an extension agent. There is no difference between the simulated models and the empirically observed models, and therefore we have to reject our hypothesis that the farther away a farmer is located vis-a-vis the location of the extension office, the less likely he or she is to be visited by an extension worker. We explain this result as that in Rwanda the feeder road networks are relatively well developed (Solange et al., 2018).

5. Discussion and policy implications

From a theoretical perspective, we have argued about the inclusion of different forms of proximity in AKIS studies. It is a limitation of this study that we were not able to test all five proximity categories. However, a review by Hermans (2021) revealed that only a minority of other studies in this field included all five proximity categories. Similarly for AKIS studies, not all proximity categories will always play a role in all types of contexts. Therefore, we view our contribution as an example of how these different proximity categorizations could be applied within an AKIS context and as a starting point to integrate them in future studies.

We have tested 6 different hypotheses. In this regard, it is important to make a distinction between the results for the informal network and the formal network. Concerning the informal network (hypotheses 1a, 2a, and 3a), we have observed a pattern that signals the possibility of how certain proximity dimensions interact. Based on our results we argue that geographical proximity only starts playing a role in the informal networks of larger villages. In those cases when the distance is a threshold effect, and second, our results might indicate the existence of social and cognitive proximity. In this regard, our results fit into some of the existing literature that the possibility of geographical isolation in dimensions. Below a certain level, geographical proximity does not play a role anymore as everybody is easily connected anyway. Farmers live closely connected, and this enables denser interactions that are based on social and cognitive proximity. In this regard, our results fit into some of the existing literature that the possibility of geographical isolation in...
larger villages will diminish the probability of committing to joint actions (Houdart et al., 2011; Pachoud et al., 2020), whereas the alternative forms of proximity (social and cognitive) can improve the level of trust between network actors (Pachoud et al., 2019), thus facilitating collective actions (Torre et al., 2019b).

This brings us finally to the issue of resilience in agroecological systems. Resilience is a very complex phenomenon, and knowledge/advice networks are only one single element of multiple potential variables to assess it (Meuwissen et al., 2019; Tittonell, 2020). This means that it is difficult to draw very strong causal conclusions for our work, especially since the earlier mentioned “proximity paradox” only further complicates matters.

Still, the structure and patterns of the social network can advance or hamper a sustainable and resilient agricultural system (Bruce et al., 2021). As such, we can still tentatively say something about how the drivers of tie formation at the micro-level, in our case framed around the different forms of proximity, can influence resilience. The network analysis on the informal advice networks in the four villages showed strongly centralized networks and this tendency was confirmed by the results of the ERGM models (through the positive preferential attachment variable). At the same time the formal advice networks showed a lot of isolates, further enhancing the profile of the farm promoters and administrative officials as the central information dispensers on how to manage BXW. These types of networks are very efficient when farmers needs are fairly uniformly distributed and when uncontroversial scientific knowledge can be distributed in a top-down fashion (Ramirez et al., 2018). However, these networks are at the same time fairly vulnerable to disruption. If one of the central nodes falls out of the network, the rest of the network will be fragmented and isolated. Similarly, the central nodes should also have the most up-to-date scientific knowledge to distribute. In the case of the BXW disease, the central nodes consisting of the administrative officials sometimes still adhere to an old, but still officially sanctioned, method of BXW management called Complete Mat Uprooting (CMU). The farm promoters in these villages had much more recent management information (called Single Stem Removal) as a better option.

Other studies point to the importance of dense local knowledge/advice networks that facilitate collective action (Pachoud et al., 2019; Torre et al., 2019b) and resilience (Tittonell, 2020). In this regard we expect more resilience in the small village communities where social and cognitive proximity play a significant role. However, the dark side of tightly linked communities is that they sometimes have difficulty in embracing new ideas for innovation. Coфre-Bravo et al. (2019) speak about the need of networks to show a certain ambidexterity: having both bonding social capital that might be the result of social and cognitive proximity and linking and bridging social capital (based on organizational proximity and structural holes) in order to enhance resilience. We acknowledge that sometimes the same variables could also be used to operationalize other forms of proximity. For example, in our case we used age as a proxy for social proximity, but depending on the context, it might be considered a proxy for cognitive proximity.

With regard to policy recommendations, this research provided solid empirical evidence to help make the targeted interventions toward the transition to the greater resilience of rural communities.

In larger villages, the promotion of mobile phones as a way of distant communication is encouraged. Here, the use of communications technology will contribute to the flow of information thus increasing the resilience of the farming community. In this case, digital communication could offer a potential option for information exchange across large distances (Fielke et al., 2020). However, this might be an expensive affair, thus not affordable for many farmers in developing countries as the level of income is low (Forenbacher et al., 2019; McCampbell et al., 2021; Sekabira and Qaim, 2017). In smaller villages, social closeness should be considered as an added advantage to transferring information that requires a higher level of trust. The BXW management information which involves banana uprooting is a good example. Since age is an important predictor of knowledge exchange connections, the development of agricultural policy should consider targeting youth by creating a sort of incentive for younger farmers (Simões, and do Rio, N. B., 2020). Furthermore, the young generation is currently benefiting from the new low-cost education policy and program in Rwanda of 12 years including primary and secondary education (Nahayo et al., 2018). Thus, engaging youth will also contribute to reducing the negative effects of a low level of education, as we have observed.

6. Conclusion

In this paper, we reviewed five different proximity concepts and operationalized them in AKIS terms. Our empirical investigation shows that the geographical proximity was significant and positively affecting knowledge exchange within the informal advice network, but was not important in the formal AKIS. This form of proximity was significant in two larger villages, signposting that geographical distance does not matter until a certain threshold is reached. In relatively smaller villages where distance is not relevant, cognitive and social proximity comes into play. The results of our study provide relevant information on the resilience of agricultural systems. For example, the highly centralized network structure with stronger preferential attachment that we found in our four villages enhances the attribute of resilience by being efficient in distributing uncontroversial scientific knowledge. In this study, we
provide empirical evidence that the proper integration of informal social networks into the existing formal extension system would result in effective knowledge exchange within systems for agricultural knowledge and innovation.

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.

Data availability

Data will be made available on request.

Appendix

Table 6

<table>
<thead>
<tr>
<th>Village</th>
<th>Test</th>
<th>Model0 (E)</th>
<th>Model1 (E + P)</th>
<th>Model2 (E + P + IL control)</th>
<th>Model3 (E + P + IL + NL control)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Karambo</td>
<td>AIC</td>
<td>1579.5</td>
<td>1494.3</td>
<td>1415.6</td>
<td>830.5</td>
</tr>
<tr>
<td></td>
<td>BIC</td>
<td>1566.4</td>
<td>1535.8</td>
<td>1471.0</td>
<td>906.6</td>
</tr>
<tr>
<td>Mururro</td>
<td>AIC</td>
<td>1399.1</td>
<td>1305.6</td>
<td>1284.7</td>
<td>821.8</td>
</tr>
<tr>
<td></td>
<td>BIC</td>
<td>1406.2</td>
<td>1348.3</td>
<td>1341.6</td>
<td>900.1</td>
</tr>
<tr>
<td>Rubira</td>
<td>AIC</td>
<td>2118.2</td>
<td>2096.0</td>
<td>1991.5</td>
<td>1239.5</td>
</tr>
<tr>
<td></td>
<td>BIC</td>
<td>2157.7</td>
<td>2141.2</td>
<td>2051.8</td>
<td>1322.4</td>
</tr>
<tr>
<td>Rusera</td>
<td>AIC</td>
<td>2608.4</td>
<td>2404.8</td>
<td>2272.8</td>
<td>1826.2</td>
</tr>
<tr>
<td></td>
<td>BIC</td>
<td>2616.9</td>
<td>2455.4</td>
<td>2340.3</td>
<td>1918.9</td>
</tr>
</tbody>
</table>

Key: E = edges, E + P = edges + proximities, E + P + IL control = edges + proximities + individual level control variables, E + P + IL + NL control = edges + proximities + individual level control + network level control variables.

References


Hardeman, S., Frenken, K., Nomaler, O., Ter Wal, A.L.J., 2015. Characterizing and comparing innovation systems by different ‘modes of knowledge production: A

Acknowledgement

This work received financial support from the German Federal Ministry for Economic Cooperation and Development (BMZ) commissioned and administered through the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) Fund for International Agricultural Research (FIA), grant number: 81219434. Frans Hermans and Milad Abbasiharofteh further acknowledge the support of the Trafotib project, funded by the German Federal Ministry of Education and Research (BMBF) grant number 031B0020. We acknowledge anonymous reviewers and the guest editor for the time invested in critically reviewing this manuscript.