Climatic Change (2023) 176:8
https://doi.org/10.1007/s10584-023-03484-6

Farmers' social networks and regional spillover effects in agricultural climate change mitigation

Cordelia Kreft[1] · Mario Angst[2] · Robert Huber[1] · Robert Finger[1]

Received: 11 May 2022 / Accepted: 10 January 2023
© The Author(s) 2023

Abstract
Climate change poses a severe threat to global agricultural production and rural livelihoods, and since agriculture itself is a significant source of greenhouse gas (GHG) emissions, it can also play an important role in climate change mitigation. This article investigates how farmers' social networks influence the adoption of on-farm mitigation strategies. More precisely, we use a network autocorrelation model to explore the relationship between a farmer's own mitigation behavior and the mitigation behavior and knowledge of his fellow farmers. The analysis is based on a regional case study in Switzerland and uses data obtained from personal network interviews combined with survey and census data of 50 farmers. Half of them are members of a local collective action initiative for agricultural climate change mitigation, while the others do not participate in the initiative. We find that, on average, farmers with a larger network adopt more mitigation measures, and furthermore, mitigation adoption is linked with the level of knowledge within farmers' networks. Indeed, the likelihood that non-members will adopt mitigation measures increases if they are closely associated with members of the collective action, suggesting a local spillover effect. It follows that strengthening knowledge exchange among farmers and supporting local farmers' initiatives can potentially contribute to the diffusion of agricultural climate change mitigation practices.

Keywords Climate change · Mitigation · Agriculture · Social networks · Knowledge exchange · Network autocorrelation models

1 Introduction

Global agricultural production is a major source of anthropogenic greenhouse gas (GHG) emissions (IPCC 2019). Consequently, since successful climate change mitigation depends primarily on the reduction of these emissions, it has become a major concern for policymakers and scientists (OECD 2013). Many countries have introduced emission reduction targets for their agricultural sector under the UN Framework Convention on Climate

✉ Cordelia Kreft
ckreft@ethz.ch

1 Agricultural Economics and Policy Group, ETH Zurich, Zürich, Switzerland

2 Digital Society Initiative, University of Zurich, Zürich, Switzerland

Change (Fellmann et al. 2018; Richards et al. 2016). However, successful GHG mitigation means that farmers must actively change and adapt their practices, for example, by adopting climate friendly practices in the on-farm management of livestock, crops, or energy utilization (Smith et al. 2008). Thus, a broad-based understanding of farmers' decision-making processes is crucial for effective mitigation and appropriate policy design.

In this article, we seek to enhance this understanding by focusing on the impact of social networks on farmers' decision-making regarding the adoption of on-farm mitigation practices. More precisely, we use a Swiss case study to investigate the link between the mitigation behavior and knowledge of socially well-connected farmers and the individuals' adoption of respective practices.

Previous research has shown that social networks influence farmers' decisions in various fields. The key assumption is that new technologies or practices spread through social learning, i.e., knowledge based on observation and interaction with peers and neighbors (e.g., Šūmane et al. 2018), also referred to as spillover or neighborhood effect (e.g., Vroege et al. 2020). For example, social relations influence the occurrence of farmers' entrepreneurship (Fitz-Koch et al. 2018) and affect decisions relating to multiple land use, innovation, and technology (e.g., Bandiera and Rasul 2006; Krishnan and Patnam 2014; Matuschke and Qaim 2009;). Several scholars found that social networks impact the adoption of agri-environmental measures (e.g., Riley et al. 2018; Skaalsveen et al. 2020; van Dijk et al. 2015, 2016) and conversion to organic agriculture (e.g., Läpple and Kelley 2015; Wollni and Andersson 2014). The existing literature has focused mainly on so-called endogenous network effects (Bandiera and Rasul 2006; Manski 2000), i.e., how farmers learn from observing the experiences of others and base their decisions on the behavior of their peers. Since data is limited, very few studies have investigated exogenous network effects, namely the impact of certain peer attributes, e.g., age, education, etc., on farmers' behavior (Keil et al. 2017; Matuschke and Qaim 2009; Murendo et al. 2018).

Recently, evidence has been found indicating positive peer influence on farmers' uptake of climate change adaptation measures (Di Falco et al. 2020). However, the role of farmers' social networks in the adoption of climate change mitigation remains largely unexplored. In particular, no study has yet investigated exogenous network effects in the context of mitigation. This constitutes an important research gap since GHG reduction practices are still relatively new to most farmers, thus making knowledge sharing and social learning particularly important, also from a policy angle. Furthermore, social networks are of great relevance for agricultural mitigation practices as they can help to promote cooperation between farmers (IPCC 2014; OECD 2012). This is essential since collaboration between farmers can reduce marginal costs of mitigation, which are usually high in the agricultural sector. For instance, economies of scale facilitate investment decisions (Bouamra-Mechemache and Zago 2015; Hodge and McNally 2000), and social learning can reduce the costs of knowledge acquisition. The coordination of land use and field operations potentially leads to efficient mechanisms for mitigation. In fact, farmers' collective action and "grassroots" innovations[1] can serve as an example to others and spread to a wider region. Up until now, the spillover effects of collective action for sustainable development have been viewed

[1] Grassroots innovations for sustainability are defined as "networks of activists and organizations generating novel bottom–up solutions for sustainable development; solutions that respond to the local situation and the interests and values of the communities involved. In contrast to mainstream business greening, grassroots initiatives operate in civil society arenas and involve committed activists experimenting with social innovations as well as using greener technologies" (Seyfang and Smith, 2007; Smith and Seyfang, 2013).

from a rather general viewpoint or in different contexts, such as local low-impact housing, renewable energy production, or car-sharing (e.g., Ornetzeder and Rohracher 2013; Smith and Seyfang 2013), and research on the spillover effects of collective action in agriculture is very limited (Vaiknoras et al. 2020).

Our research contributes to this literature by exploring the characteristics of farmers' personal networks with regard to exchange of knowledge related to agricultural climate change mitigation and their association with the actual uptake of mitigation measures. Our research aims to assess the role of farmers' cooperation and collective action in the context of agricultural climate change mitigation, which constitutes a key challenge facing the agricultural sector. We apply a network autocorrelation model to study potential network influence processes and local spillover effects of a farmers' climate protection initiative. We thereby account for the strength and type of relationships, as well as specific, relevant characteristics of network members. More specifically, we use a Bayesian approach which allows us to model multiple influence processes and compare them simultaneously (Dittrich et al. 2020). Control variables such as age, education, farm type, or perceived self-efficacy are used at the individual farmer level to account for possible correlated effects which do not reflect social interactions (Kreft et al. 2021a, 2021b; Wuepper et al. 2019). Our analysis is based on a combination of census, survey, and detailed network data. The latter was obtained through tablet-based face-to-face interviews with 50 farmers in a Swiss region.

Our main contributions are threefold: Firstly, we investigate how social learning among connected farmers influences the adoption of on-farm climate change mitigation measures. Secondly, we assess how the presence of climate change mitigation knowledge within farmers' personal social networks affects their adoption decisions. Thirdly, we explore how the spillover of a local farmers' collective climate protection action group influences the adoption of mitigation measures in the wider region. Our results help to deepen the understanding of farmers' adoption decisions in the context of agricultural climate change mitigation and highlight the role of social networks. This can help to inform policymakers when deciding upon effective and efficient policy instruments to incentivize climate friendly agriculture.

The remainder of this article is as follows: Section 2 provides the theoretical background on farmers' social networks and adoption of agricultural climate change mitigation as well as the hypotheses tested in this article. Section 3 introduces the autocorrelation model used for assessing the associations between certain network characteristics and mitigation adoption. Section 4 describes the case study followed by Section 5, which presents data and data collection. Section 6 contains descriptive and estimation results and is followed by a discussion in Section 7 and conclusions in Section 8.

2 Theoretical background and conceptual framework

Our conceptual framework is based on the social network theory (Borgatti and Ofem 2010) and the concept of social learning (Foster and Rosenzweig 1995) whereby it is assumed that individual behavior is influenced by interaction with peers, also referred to as herd behavior, spillover, neighborhood, or peer effect (e.g., Granovetter 1978). Three possible network effects can be identified: endogenous effects (impact of network members' behavior), exogenous effects (impact of network members' characteristics), and correlated effects (resemblance between individual's behavior and that of their network due to similar environment, e.g., access to the same extension service) (Keil et al. 2017; Manski 2000). The first two effects can, to some extent, be explained by social learning, essentially defined as learning by observing others and interacting with them.

2.1 The role of social networks in farmers' adoption behavior

The analysis of farmers' social networks and social learning has emerged as a key tool for understanding adoption decisions. In general, close ties to other farmers facilitate knowledge spillovers and information flow related to new agricultural technologies, such as improved seeds and varieties (e.g., Conley and Udry 2010; Krishnan and Patnam 2014) or knowledge-intensive practices such as no-tillage farming (e.g., Ingram 2010; Skaalsveen et al. 2020).

However, whether and how social learning actually occurs depends on many factors such as the complexity of the technology (Wuepper et al. 2017), heterogeneity of farming conditions (Munshi 2004), number of adopters (Bandiera and Rasul 2006), or structure of the network. For example, centralized networks and links to key actors are found to facilitate the rapid diffusion of information (Peres 2014). Since most farmers prefer to seek advice from key network members rather than from less connected colleagues, core-periphery network structures are often observed, i.e., farmers who are less connected most frequently approach a small group of socially well-connected key farmers when seeking advice (Isaac et al. 2007). Generally, a dense, widely connected network promotes successful collaboration (Bodin and Crona 2009). At the same time, relations to disparate groups might provide novel information and thus encourage innovation (Levy and Lubell 2017).

To date, there are few studies which focus on both endogenous network effects and the potential exogenous effects of farmers' social networks (Matuschke and Qaim 2009; Murendo et al. 2018). Only one study found evidence that network members' characteristics (namely education level) influence individual farming behavior (adoption of no-till practices) (Keil et al. 2017). However, the influence of exogenous effects on adoption decisions might depend on the specific situation and technologies.

2.2 Agricultural climate change mitigation and farmers' collective action

Farmers' collective action is increasingly recognized as an important approach to the management of agri-environmental problems (Bamière et al. 2013; Dupraz et al. 2009; Mills et al. 2011; Prager 2012, 2015; Vanni 2013). Similarly, it could also enhance effective strategies for agricultural climate change mitigation. Firstly, a single farmer's efforts are simply not enough to reduce GHG emissions to any significant extent (OECD 2012, 2013). Secondly, GHG reduction is assessed as a classic collective action problem including challenges, such as freeriding, which can be overcome by farmers' collaboration (Agarwal and Dorin 2017; Ostrom 1990; Stallman 2011). Given that climate change mitigation often involves new and unfamiliar measures, the role of knowledge exchange within farmers' networks is particularly important and can potentially shape perceptions on costs, risks, and benefits of mitigation. Moreover, this learning and knowledge sharing can spread beyond the scope of the collective action scheme through ties between members and non-members (Bernard and Spielman 2009; Ornetzeder 2001).

2.3 Hypotheses: network effect, knowledge diffusion, and collective action spillover

Based on the theory outlined above and findings from previous empirical research, we derive three hypotheses (supplementary material, Figure S1):

1. ***Endogenous network effect hypothesis (H1)***

Farmers' adoption of mitigation strategies is positively associated with strong social ties to other farmers who have adopted mitigation practices.

2. ***Knowledge diffusion hypothesis—exogenous effect (H2)***

Farmers' adoption of mitigation strategies is positively associated with strong social ties to farmers they deem to be knowledgeable about agricultural climate change mitigation.

3. ***Collective action spillover hypothesis (H3)***

Farmers' adoption of mitigation strategies is positively associated with ties to farmers participating in a collective action scheme to reduce agricultural GHG emissions.

3 Methods

All of our hypotheses describe social influence processes linking network structure (exchange relations of farmers) with individual level traits (adoption of mitigation strategies). An inherent feature of analyzing social influence processes in networks is that it cannot be assumed that the traits of interest (the dependent variable, here farmers' adoption of mitigation strategies) are independent from each other. In fact, we explicitly want to study how the expression of a dependent variable y_i of an actor i is associated with its expressions y_j, y_k in an actor's network contacts j and k. Therefore, we test our hypotheses using a network autocorrelation model (Dittrich et al. 2020).

Network autocorrelation models are an extension of normal regression models, which integrate one or more network autocorrelation parameter capturing the processes through which we assume network influence to occur. The network autocorrelation is estimated by specifying one or multiple weight matrices W to capture our theoretical models of influence relations. These weight matrices are used to add a weighted sum of attributes for an actor's network neighbors to the linear predictor of the regression model for each actor. For a single influence process acting through W, with g actors in a network, the model can be written as:

$$y = \rho W y + X\beta + \epsilon, \epsilon \sim N(0g, \sigma 2Ig) \tag{1}$$

where ρ is the network autocorrelation parameter capturing the strength of the network influence process. X is a covariate matrix as in a standard linear regression (capturing other, actor-level covariates that the model adjusts for) with associated regression coefficients in the β vector. The error terms are assumed to be independent and identically distributed[2].

We use a recently proposed, new Bayesian implementation of the network autocorrelation framework (Dittrich et al. 2020) that allows us to test our hypotheses by simultaneously estimating parameters relating to the strength of different autocorrelation processes occurring within four sub-networks of the overall network. Testing our hypotheses within this framework implies the use of four different model specifications.

The first model, corresponding to Eq. (1) (simple network influence), is a first-order network autocorrelation model containing a single network weight matrix to estimate network autocorrelation understood as a single process acting uniformly throughout the whole network. If we choose a weight matrix W to measure relations among farmers and the strength of these relations, an initial test of H1 can be carried out based on the resulting posterior distribution of ρ.

The second model, corresponding to Eq. (2), adds the coefficient $\beta_{\text{net\_knowledge}}$ estimating the association between the aggregated knowledge of network contacts about climate change mitigation and farmers' mitigation behavior. The model still uses the form described in (1), and the coefficient is estimated based on a variable in the covariate matrix X. The posterior distribution of $\beta_{\text{net\_knowledge}}$ allows for a test of H2.

$$y = \rho Wy + X\beta + x\beta_{\text{net}_{\text{knowledge}}} * \beta_{\text{net}_{\text{knowledge}}} + \epsilon, \epsilon \sim N(0g, \sigma 2Ig) \tag{2}$$

The third model is a fourth-order network autocorrelation model (3), which assumes different strengths of network autocorrelation within and between collective action participants and non-participants. To this end, the adjacency matrix W is rearranged into four weight matrices W_{aa}, W_{ab}, W_{bb}, and W_{ba}, which only contain entries on their respective process of interest and are separately row-standardized (Dittrich et al. 2020). W_{aa} denotes the sub-network of relations among participants and W_{bb} among non-participants, and W_{ab} and W_{ba} indicate an exchange between groups.

With the collective action participants as a network subgroup a and non-participants as subgroup b, the model takes the form:

$$\begin{aligned} y = \begin{bmatrix} y_a \\ y_b \end{bmatrix} &= \begin{bmatrix} \rho_{aa} W_{aa} & \rho_{ab} W_{ab} \\ \rho_{ba} W_{ba} & \rho_{bb} W_{bb} \end{bmatrix} \begin{bmatrix} y_a \\ y_b \end{bmatrix} + X\beta + \varepsilon \\ &= \left(\rho_{aa} \begin{bmatrix} W_{aa} & 0 \\ 0 & 0 \end{bmatrix} + \rho_{bb} \begin{bmatrix} 0 & 0 \\ 0 & W_{bb} \end{bmatrix} + \rho_{ab} \begin{bmatrix} 0 & W_{ab} \\ 0 & 0 \end{bmatrix} + \rho_{ba} \begin{bmatrix} 0 & 0 \\ W_{ba} & 0 \end{bmatrix} \right) \begin{bmatrix} y_a \\ y_b \end{bmatrix} \\ &+ X\beta + \varepsilon \end{aligned} \tag{3}$$

where y_a and y_b contain values of the dependent variable (adoption of mitigation practices) for participants and non-participants, respectively. The associated network autocorrelation ρ_{aa}, ρ_{bb}, ρ_{ab}, and $\rho_{ba}$are measured for the strength of autocorrelation within and between these sub-networks. When combined, they constitute a more differentiated test of H1, relaxing the assumption of a homogeneous network influence process. Further, ρ_{ba} is a measure for the strength of autocorrelation acting on values y_b of non-participants based on their relations to collective action participants. The posterior distribution of ρ_{ba}thus tests for H3, the collective action spillover hypothesis.

[2] Note that there is an alternative variant of the model in which autocorrelation is modeled by specifying autocorrelation in the error terms and which has a slightly different interpretation (see, e.g., Leenders (2002)).

The fourth model includes $\beta_{net\_knowledge}$ to assess the extent to which the collective spillover effect might be due to unevenly distributed knowledge throughout the sub-networks and vice versa. This can be tentatively assessed in the change in ρ_{ba} after adjusting for $\beta_{net\_knowledge}$. The adjusted model takes the following form:

$$
\begin{aligned}
y = \begin{bmatrix} y_a \\ y_b \end{bmatrix} &= \begin{bmatrix} \rho_{aa} W_{aa} & \rho_{ab} W_{ab} \\ \rho_{ba} W_{ba} & \rho_{bb} W_{bb} \end{bmatrix} \begin{bmatrix} y_a \\ y_b \end{bmatrix} + X\beta + x\beta_{net_{knowledge}} * \beta_{net_{knowledge}} + \varepsilon \\
&= \left(\rho_{aa} \begin{bmatrix} W_{aa} & 0 \\ 0 & 0 \end{bmatrix} + \rho_{bb} \begin{bmatrix} 0 & 0 \\ 0 & W_{bb} \end{bmatrix} + \rho_{ab} \begin{bmatrix} 0 & W_{ab} \\ 0 & 0 \end{bmatrix} + \rho_{ba} \begin{bmatrix} 0 & 0 \\ W_{ba} & 0 \end{bmatrix} \right) \begin{bmatrix} y_a \\ y_b \end{bmatrix} \\
&+ X\beta + x\beta_{net_{knowledge}} * \beta_{net_{knowledge}} + \varepsilon
\end{aligned} \tag{4}
$$

All models were fit using the code provided in Dittrich (2020), which implements a Metropolis-Hastings algorithm to obtain the posterior distribution of model parameters in the statistical programing environment R (R Core Team 2021). We used a recommended (multivariate) normal prior distribution with a mean of 0.1 and standard deviation of 1 for the network autocorrelation parameters and uninformative priors for all other parameters. We evaluated the model based on 5000 draws from the posterior (with a burn-in of 100 for the Metropolis-Hastings algorithm). All code and anonymized data needed to replicate the analysis, as well as additional sensitivity checks, can be accessed in a public, open repository under https://doi.org/10.5281/zenodo.7401318.

4 Case study

Our case study is located in the northern part of Canton Zurich in Switzerland. Agricultural production is quite diverse and ranges from dairy and meat production to arable crops, viticulture, fruit, and vegetables (Kreft et al. 2021a). The region is home to the farmers' initiative AgroCO_2ncept Flaachtal, which aims to collectively reduce agricultural GHG emissions.[3] It is currently one of very few examples of collective climate change mitigation in agriculture. The project was founded in 2011 in a bottom-up process on the initiative of a single farmer, who was able to convince some colleagues to collaboratively reduce agricultural GHG emissions. Strategies for on-farm climate change mitigation were elaborated with the help of agricultural experts and extension services. In spring 2012, the project was opened for the participation of more farms. Since 2016, the Swiss Federal Office for Agriculture supports AgroCO_2ncept, guaranteeing financial support during 6 years for a maximum of 30 participating farms (BLW 2018). Participation is independent of farm type, farming system, or current emission level. At present, 25 farmers on 23 farms (two farms have multiple owners/managers) participate actively in AgroCO_2ncept.[4] The declared goal of AgroCO_2ncept is to achieve a 20% reduction in the aggregated overall GHG emissions from participating farms by 2022 as compared to 2016. This refers to an amount of 4500 t of CO_2-equivalents mitigated by the end of the 6-year project period. The project comprises a focus on 39 measures in different fields, i.e., crop production (14

[3] https://www.agroco2ncept.ch

[4] Since one farmer no longer actively participates but is still a passive member of the association, sometimes 26 participating farmers on 24 farms are mentioned. As the respective member did not participate in the interviews either, we refer here to only 25 active AgroCO2ncept members on 23 farms. The latter means that two farms have two farm managers each, i.e., in total 4 farmers manage 2 farms.

measures), livestock farming (12), and energy use (13) (Kreft et al. 2020). When a farm joins the project, its current emission levels are assessed (status-quo assessment), and the farmer then receives extensive advisory service to choose the mitigation measures best suited to the farm's specific structures and needs. The farmer receives a compensatory payment for each mitigation measure implemented. This procedure is designed to ensure mitigation efficiency tailored to the individual farm as no measures are stipulated and farmers can choose those most appropriate for their farm.

AgroCO$_2$ncept aims to prove that practical on-farm climate change mitigation has large potential for an effective reduction of GHG emissions in the agricultural sector. The initiative seeks to set an example for other farmers in the region and beyond. The central idea is that mitigation in agriculture cannot be achieved by single measures implemented by individual farmers but demands collective action and aggregated reduction targets beyond the single farm level. At the same time, mitigation should not result in productivity or income losses (AgroCO$_2$ncept 2016). AgroCO$_2$ncept embodies the characteristics of a local collective action scheme based on social ties among farmers and is perfectly suited as a case study for the hypotheses we want to test in this article.

5 Data collection and variables

5.1 Data collection

We interviewed 50 farmers, 25 of whom participate in the AgroCO$_2$ncept initiative and 25 non-participants located in the same region. The 25 non-participating farmers were chosen based on their proximity to the region of Flaachtal, where most of the AgroCO$_2$nept farmers are located. [5]

Interviews were structured and conducted based on a questionnaire. The interviews took place in November and December 2019. They lasted between 20 and 40 minutes and were carried out on site by four trained interviewers. The questions were asked and simultaneously shown to the respondents on a tablet. Answers were directly entered via touch screen by the respondent or the interviewer.

We created the interview protocol using the newly developed digital network survey tool Network Canvas (https://networkcanvas.com). It is a free and open-source software designed to collect network data in a partly participatory way through intuitive and appealing visualizations and touch screen applications (Complex Data Collective 2016). This can help to make interviews less tedious and also reduces respondent burden (e.g., Eddens et al. 2017). Moreover, as the interviewees could enter certain answers themselves, particularly those related to potentially sensitive network information, it was possible to reduce the effects of social desirability and satisficing, which can lead to data inaccuracy (Perry et al. 2018). Structure, user-friendliness, and understanding of the interview questionnaire were pre-tested with three social network experts and six students of agricultural sciences.

The questionnaire contained 29 questions for AgroCO$_2$ncept participants and 25 questions for non-participants and included the following sections: (i) personal characteristics of the respondent, (ii) agricultural climate change mitigation on the respondent's farm,

[5] Figure S2 in the supplementary material shows a map with the spatial location of the interviewed farms.

(iii) roster[6] and name generator questions to identify other farmers (alters) with whom the respondent communicates on agricultural climate change mitigation, including frequency of these exchanges, (iv) attributes of named alters (name interpreter), (v) relations among the named alters (alter-alter relations), and (vi) influential alters, based on the respondent's perception. An additional roster containing the names of all AgroCO_2ncept members was presented to non-participants to assess the contact between non-participants and participants.

The complete questionnaires, all resulting data sets plus the codebooks explaining the variables, are available in Kreft et al. (2021b) and freely accessible on the ETH Research Collection: https://www.research-collection.ethz.ch/handle/20.500.11850/458053.

We supplemented the tablet-based interview data by incorporating data from previous work. We were able to match the data of 46 of the 50 interviewees with existing data from a larger survey on farmers' adoption of climate change mitigation measures and behavioral characteristics such as climate change concerns and non-cognitive skills, as well as census data on farm structures and demographics (Kreft et al. 2020).

5.2 Variables

Table 1 gives an overview of the variables used in our analysis as well as their summary statistics within our sample. More precisely, it shows the dependent variable of mitigation adoption and the relevant network variables as well as all additional covariates, i.e., farmers' behavioral characteristics, demographics, and farm structural characteristics. Details relating to the covariates included are presented in the supplementary material to this article.

The dependent variable of interest is defined as the share of mitigation measures adopted out of all those measures which are suitable for the farm type. In a previous survey, 13 mitigation measures were chosen based on GHG reduction potential, relevance, and suitability for Swiss agriculture (Kreft et al. 2020).[7] We use the frequency of exchanges regarding agricultural climate change mitigation as the basis for testing the endogenous network effect hypothesis (H1) which implies an association between strong social ties and the adoption of mitigation strategies. Frequency of exchange is assessed by an ordinal variable with five levels.[8] We conceptualize exchange as an inherently reciprocal concept and thus calculate the presence and strength of an undirected dyadic exchange relation $E_{u_{ij}}$ between any two survey respondents i and j, as the mean of their respective answers regarding the strength of their exchange E_d; thus, $E_{u_{ij}} = E_{u_{ji}} = \frac{E_{d_{ji}}+E_{d_{ij}}}{2}$. A value of 0 indicates the absence of exchange. We row-standardized the undirected, weighted network adjacency matrix capturing the network of exchange relations among farmers (Leenders 2002) to construct the 50×50 (given that n=50) weight matrix W.

We rely on the aggregate assessment of a farmer's mitigation knowledge, as rated by others, to test the knowledge diffusion hypothesis (H2) which suggests an association between the mitigation knowledge of network contacts and adoption of mitigation

[6] A roster is a list of names from which the interview participants are asked to choose their relevant contacts. It can only be applied when the network boundary is clear and all overall network members are previously known.

[7] For further information on mitigation measures, please refer to the supplementary material (Table S1).

[8] 1 = once per year; 2= every few months; 3 = once per month; 4 = once per week; 5= every day

Table 1 Overview and summary statistics of variables included in the model

Variable	Variable specification	Total sample	Farmers participating in AgroCO2ncept	Farmers not participating in AgroCO2ncept
Number of respondents (*n*)		50	25	25
Dependent variable				
Mitigation adoption	Share (0–100%) of mitigation measures adopted from all potential measures suitable for the specific farm type (Mean and (SD))	0.41 (0.19)	0.43 (0.19)	0.39 (0.19)
Network variables				
Frequency of contact (realized)	Ordinal variable: 1= once per year; 5= every day	1.71 (1.23)	2.32 (0.92)	1.31 (1.24)
Network knowledge	Climate change mitigation knowledge of network contacts Ordinal variable: 1= knows nothing; 5= knows a lot	3.98 (0.72)	3.97 (0.70)	4 (0.77)
Farmers' behavioral characteristics				
Non-cognitive skills (self-efficacy and locus of control beliefs)	Ordinal variable: 1= very low; 5= very high (mean and (SD)) (for modeling, a factor variable is created)	3.35 (0.88)	3.74 (0.73)	2.96 (0.85)
Climate change concerns; Swiss agriculture	Assessment of climate change consequences for future of Swiss agriculture as a whole Ordinal variable: 1= very negative; 5= very positive (mean and (SD))	4.06 (0.77)	4.2 (0.65)	3.92 (0.86)
Climate change concerns: farm	Assessment of climate change consequences for future of own farm Ordinal variable: 1= very negative; 5= very positive (mean and (SD))	3.6 (0.83)	3.68 (0.75)	3.52 (0.92)
Farmers' demographic characteristics				
Age	Age of the farmer in 2019 (mean and (SD))	52 (6.33)	48 (7.39)	55 (6.6)
Distribution of education levels	Categorical variable			
Agricultural apprenticeship		24	9	15
Agricultural master certificate		14	10	4
Agri-technician		3	2	1
Technical college, university		5	3	2

Table 1 (continued)

Variable	Variable specification	Total sample	Farmers participating in AgroCO2ncept	Farmers not participating in AgroCO2ncept
Missing		4	1	3
Farm structural characteristics				
AgroCO$_2$ncept	Participation (0,1)	25	25	0
Farm type	Categorical variable (in model: arable farming and livestock, all others as baseline)			
Arable Farming		9	5	4
Livestock		29	16	14
Special crops		4	3	1
Others		4	1	3
Missing		4		3
Farm size	Total agricultural land in ha (mean and (SD)) (for modeling, the log is used)	34.70 (27.37)	44.26 (33.92)	24.73 (13.86)

strategies. Respondents were asked to evaluate their exchange partners' knowledge about agricultural climate change mitigation on a 5-point ordinal variable (from knows nothing to very knowledgeable). Since each farmer was rated on the basis of the mean score assigned to them by their various exchange partners, the score is a crowd-sourced assessment of farmers' knowledge, as evaluated by their peers. Finally, we calculated the sum of the knowledge scores of all peers to assess the combined knowledge of a farmer's network contacts, the main point of interest for H2. This approach helps to corroborate farmers' individual assessment of their peers' knowledge and to obtain a more realistic estimate.

A binary variable was created for each farmer indicating participation (1) and non-participation (0) in the collective action scheme AgroCO_2ncept to test the collective action spillover hypothesis (H3) relating to its potential impact on adoption of mitigation strategies over the wider network. Based on the network of exchange relations among farmers, this allows us to effectively divide the network into four components. One component describes the network of exchange relations among participants, a second component relates to networking among non-participants, and a third and fourth component cover networks (and hypothesized influence pathways) from participants to non-participants and vice versa. Accordingly, the adjacency matrix W is rearranged into four weight matrices, which are separately row-standardized (Dittrich et al. 2020, p. 175).

6 Results

6.1 Descriptive network statistics

Table 2 summarizes the descriptive statistics of the total network and the two sub-networks (i.e., AgroCO_2ncept participants and non-participants).

Each sub-network comprises 25 nodes (farmers). There are 133 edges (based on exchanges about climate change mitigation) between all farmers in the whole network, whereby the network of AgroCO_2ncept participants is much denser (74 ties) than that of non-participants (6 ties). This is partly due to the different approaches of data collection for the two groups of participants (roster vs. free name-generator). There are 53 ties between the two sub-networks. The majority of ties are workmates, club colleagues, and friends, while some of these also overlap (see Figure S3 in the supplementary material for more information on tie distribution and overlap). On average, ties are slightly stronger in the AgroCO_2ncept network (1.6), i.e., exchanges are more frequent than in the overall network (1.3).

Table 2 Statistics of farmers' networks

	Total network	Network of AgroCO_2ncept participants	Network of non-participants
Number of nodes	50	25	25
Number of edges	133	74	6
Mean tie-strength	1.3	1.6	1.3

The degree of centrality (between 0 and 1) depicts just how centralized a network is. A maximally centralized network is star-shaped with only one central actor connected to everyone else (Freeman 1979). The AgroCO$_2$ncept network is much more centralized (0.7) than the total network (0.4).[9] This is mainly due to the fact that the initiative was originally set up and formed by one to three central actors (see Figure S4 in the supplementary material for additional information on the distribution of degree centrality).

Figure 1 gives a visual impression of the networks. Black dots represent AgroCO$_2$ncept participants, and gray dots refer to non-participants. The ties connecting the farmers capture regular exchange about climate change mitigation and are weighted by frequency of contact. Larger nodes depict higher shares of adopted mitigation measures. As mentioned before, some ties exist between the two sub-groups, indicating a strong integration of AgroCO$_2$ncept members within the region.

Figure 2 shows four scatterplots capturing important features of farmers' individual networks in relation to their mitigation adoption. The size of the network (number of ties) increases along the mitigation gradient, i.e., farmers who adopt more mitigation measures have larger exchange networks. The mean strength of all ties in a farmers' network is relatively independent of mitigation adoption with most farmers exchanging on mitigation with their peers once or a few times per year. Betweenness centrality measures the number of shortest paths that go through a node, in other words the extent to which the actor controls the flow of information within the network (Freeman 1979). In our sample, betweenness centrality of farmers increases with mitigation adoption, i.e., farmers adopting more mitigation measures have more shortest paths going through them.

Moreover, the mean mitigation share of contacts correlates with farmers' own mitigation: the contacts of high adopters have a higher share of adopted mitigation measures than the contacts of low adopters.

6.2 Network autocorrelation estimation results

Figure S6 shows the results of the four network autocorrelation models in the form of a coefficient plot. Our report covers the network variables of greatest interest. A coefficient plot with all covariates and a detailed table showing the coefficient magnitude and confidence interval of all variables can be found in the supplementary material to this article (Figure S5 and Table S1).

Our results indicate that there is uncertainty regarding both the sign and magnitude of the endogenous network association effect (H1) specified as a homogenous process across the whole network (averaged network influence). The averaged mean of the network influence is around zero in both the simple influence model and also after adjusting for knowledge diffusion ((1) and (2), Fig. 3)). It is just as likely to be positive as it is to be negative, and the 88% credible interval is evenly distributed around zero, containing both small and larger estimates.

We find a reliably positive effect for the association of aggregated knowledge about climate change mitigation in a farmer's network contacts (H2) throughout both models containing the parameter (knowledge diffusion model and fourth-order model plus knowledge diffusion ((2) and (4), Fig. 3)). The probability of a positive association is high. In terms of magnitude, the posterior mean indicates a relatively significant effect (the effect should be interpreted as the ceteris paribus change given a one standard deviation increase and

[9] However, the centralization of the network of non-participants should not be interpreted substantively, given the size of the network.

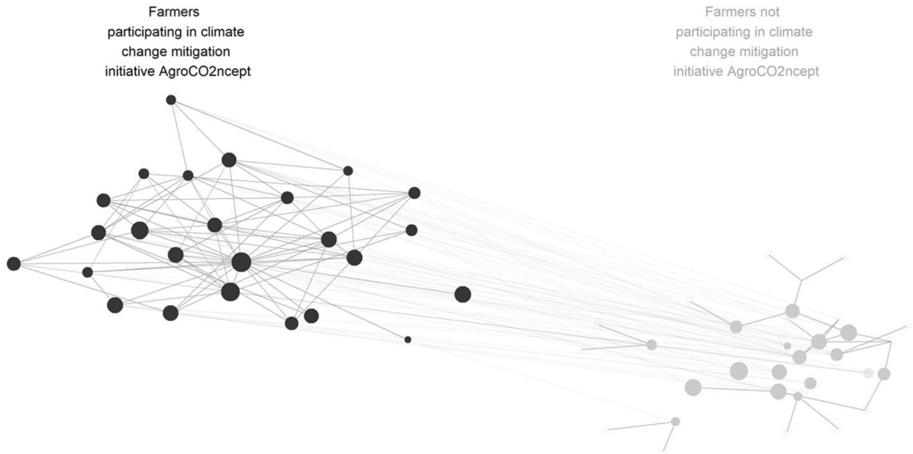

Fig. 1 Total network ties regarding regular exchange on agricultural climate change mitigation. Black dots represent AgroCO$_2$ncept participants, and gray dots represent non-participants. The size of the nodes represents the share of adopted mitigation measures. The strength of the connecting lines represents the frequency of exchange

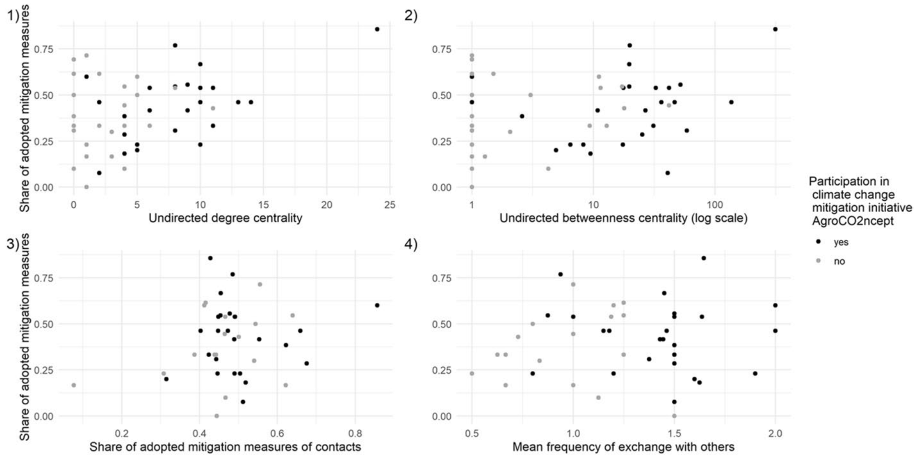

Fig. 2 Farmers' individual mitigation adoption against different network traits. Black dots represent AgroCO$_2$ncept participants, and gray dots represent non-participants. The *y*-axis shows the share of adopted mitigation measures compared to the possibly relevant number of measures for the respective farm type. The *x*-axis represents four different characteristics of farmers' personal networks: **1** undirected degree centrality (number of ties), **2** undirected betweenness centrality (number of shortest paths going through the node), **3** share of adopted mitigation measures of contacts, and **4** share of adopted mitigation measures of contacts

considering that values of y_i can range between 0 and 1). However, the credible interval also contains relatively small parameters.

Moreover, we find evidence for the collective action hypothesis (H3) in both fourth-order models ((3) and (4), Fig. 3)). It is almost certain that the relevant parameter ρ_{ab} (influence of AgroCO$_2$ncept on non-participants network, Fig. 3) is positive, given the

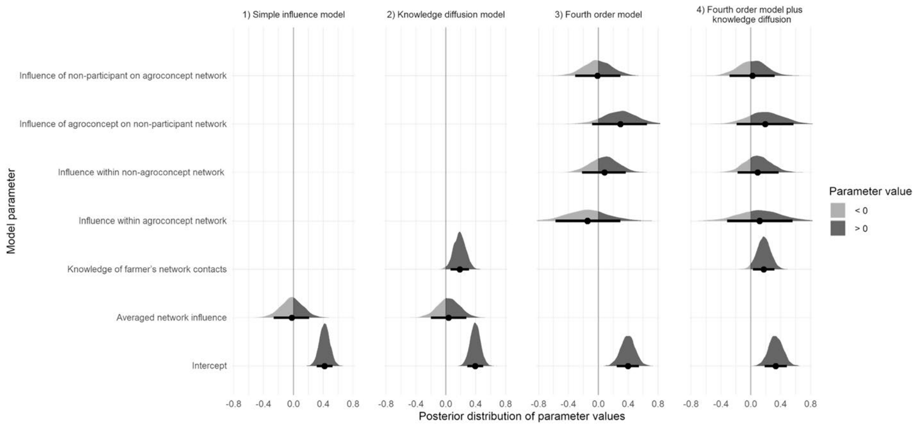

Fig. 3 Estimated posterior distribution of network-related parameters for the four models tested. Network influence parameters each capture the impact of the adoption of climate change mitigation measures in a farmer's contact network on the farmer's own adoption of measures, either on average across the whole network (averaged network influence) or within and between sub-networks. The parameter for knowledge of network contacts can be interpreted as the marginal effect of a one unit increase in knowledge about mitigation measures among a farmer's network contacts on the share of adoption of climate change mitigation measures predicted for a farmer. Points represent median parameter estimates and horizontal spikes the 88% credible interval. Curves represent the distribution, with light gray areas for negative parameter values and dark gray areas for positive values. The posterior distribution for each parameter captures the uncertainty the model assigns to the parameter's influence. For example, a relatively wide distribution centered around zero indicates that the model fit neither supports a strong belief in the parameter having a certain sign (positive or negative) nor in the magnitude of its effect. In contrast, for example, if the posterior distribution covers a smaller range of large values and contains only few negative values, the model fit supports a stronger belief in the effect being both large and positive

proportion of its posterior distribution which is positive. Again, the magnitude of the effect is slightly uncertain, given our sample size. Nevertheless, our models justify the assumption of some, potentially influential, collective action spillover. Interestingly, the model results are much more inconclusive for all other network autocorrelation parameters in the fourth-order model. This would suggest that there is little endogenous network influence beyond the collective action spillover effect. This finding justifies the application of a network autocorrelation model that can differentiate various influence processes and does not assume a uniform process acting throughout the network.

7 Discussion

Based on a regional case study, this article investigates the suggestion that farmers' decisions on the adoption of climate change mitigation measures are influenced by the behavior and characteristics of their social network. We used a comprehensive data set comprising survey, census, and interview data. This means that the sample was rather small given the task of face-to-face interviews. However, it suffices for the purpose of this study, which aims to explore a specific regional famers' network and local influence of the collective action initiative AgroCO$_2$ncept. In our model, we account for this using a Bayesian approach, which is ideal for small networks as it does not rely on asymptotic approximations for standard errors (Dittrich et al. 2020). However, larger studies would be needed to provide more conclusive evidence and reduce any remaining doubts about the magnitude of estimated effects resulting from the smallness of our sample. The descriptive analysis of the entire network shows that AgroCO$_2$ncept participants maintain closer connections with each other than non-participants. However, the comparison between the two groups must be treated with caution given the different approach applied for the network data collection: AgroCO$_2$ncept members were provided with a full roster containing the names of all other participants from which they could select the exchange contacts they considered relevant. In addition, they could name any other persons they thought appropriate. Since there was no pre-defined network boundary for non-participants, they were asked to name, off-the-cuff, persons with whom they had regular exchanges on the topic. As it is far easier to identify names from a roster than to remember people spontaneously, this method can lead to potential recall bias (Brewer 2000). During the interviews, this effect was counteracted by prompting respondents and repeating the question several times (Adams et al. 2021).

The descriptive analysis of farmers' individual networks revealed that, on average, farmers with a larger exchange network adopt more mitigation measures. This is in line with previous literature showing a positive influence of social networks on, e.g., adoption of agri-environmental measures (e.g., Mathijs 2003; Moschitz et al. 2015; Riley et al. 2018; Schneider et al. 2009; van Dijk et al. 2015, 2016).

In addition, our detailed data set enabled us not only to explore potential endogenous network effects, i.e., the influence of the mitigation behavior of peers, but also to investigate exogenous network effects, i.e., the influence of certain characteristics of farmers' contacts. This differentiation is quite important since we find no evidence for a uniform association between the mitigation adoption of peers and farmers' own adoption across the whole network. However, we do find a positive association between adoption and strong ties to farmers who are knowledgeable about agricultural climate change mitigation.

In contrast to previous studies (Matuschke and Qaim 2009; Murendo et al. 2018), our findings indicate that adoption depends more strongly on mitigation knowledge existing within farmers' personal networks than on the actual mitigation behavior of peers. However, the type of technology or practice may determine the extent to which the characteristics of peers influence adoption (Murendo et al. 2018; Wuepper et al. 2017). We identify two main reasons which can possibly explain this phenomenon in the specific context of agricultural climate change mitigation. Firstly, the topic is still quite a relatively new, unexplored option for many farmers in Switzerland, and misconceptions regarding mitigation measures (e.g., their efficacy) represent one of the major barriers to adoption (Karrer 2012; Peter et al. 2009). Consequently, information and social learning through knowledge exchange are crucial for mitigation adoption. Secondly, many agricultural mitigation practices are not specifically tailored to the reduction of GHG emissions but primarily target other agri-environmental objectives, e.g., no-tillage to increase soil fertility (Smith et al. 2007). This makes it difficult for farmers to recognize and imitate mitigation behavior of their peers and neighbors since it may not be easy to identify the implemented measures as such. Again, in this situation, an active exchange of knowledge could play a vital role in the adoption decision.

However, knowledge of peers is based on farmers' statements and can thus be prone to measurement error since farmers might not be able to accurately assess their contacts' mitigation knowledge. We try to counteract this potential inaccuracy by taking the mean of the knowledge ascribed to a person by all connected farmers in the network. Moreover, we argue that farmers' perception of their peers' knowledge is the relevant parameter for behavioral change (Matuschke and Qaim 2009).

We also explored how the climate protection initiative AgroCO_2ncept influenced mitigation behavior of non-participating farmers in the region. Our findings indicate that mitigation by farmers who belong to AgroCO_2ncept has a positive impact on mitigation adoption of connected farmers who are not part of the initiative. Hence, in addition to our first results, we find evidence for an endogenous network effect in part of the network (i.e., only from AgroCO_2ncept members to non-members). This is possibly explained by the fact that farming practices adopted by AgroCO_2ncept farmers are more clearly related to climate change mitigation since the project and its climate protection objectives are well known in the region. Thus, identification of mitigation measures, observation, and finally imitation of measures implemented by AgroCO_2ncept members is easier than the observation of (potentially less obvious) mitigation behavior of peers who are not part of the initiative. Hence, our result suggests a local spillover effect of the collective action initiative. Therefore, we also see our study as a contribution to the literature on the spread of collective grassroots innovations, which is still relatively limited in the agricultural context (Ornetzeder and Rohracher 2013; Seyfang and Smith 2007; Vaiknoras et al. 2020).

Finally, social networks can help to overcome economic barriers of mitigation adoption through collaborative action (Bouamra-Mechemache and Zago 2015). This is particularly relevant where potentially high investments as well as transaction costs might prevent the adoption of climate change mitigation measures (Wreford et al. 2017).

8 Conclusions

In this article, we analyzed social network data of 50 farmers in a region of Switzerland and explored the relationship between social relations regarding knowledge exchange and the uptake of on-farm climate change mitigation. In general, we find that farmers with larger networks adopt more climate change mitigation measures. Our results indicate that the level of mitigation knowledge present within a farmer's network is crucial for mitigation adoption. However, it seems that farmers attach less importance to the actual mitigation behavior of peers when deciding on their own adoption of mitigation measures. We also find that strong ties to members of the regional farmers' initiative AgroCO_2ncept Flaachtal are positively associated with mitigation uptake, suggesting a local spillover effect. In contrast to our findings regarding the whole network, the actual mitigation behavior of AgroCO_2ncept members is relevant for the mitigation adoption of connected non-members.

Our findings have policy implications. We show that social network integration, and especially knowledge diffusion within such networks, can contribute to a better understanding of farmers' decision-making with regard to climate change mitigation. This is particularly important for effective policy designs aiming at a reduction of GHG emissions in agriculture. More specifically, policymakers should be aware of the relevance of social learning and informal knowledge exchange in farmers' mitigation adoption. In a relatively new field of practice, such as on-farm climate change mitigation, accumulation and exchange of knowledge with well-informed peers and neighbors can contribute to behavioral change. Therefore, the creation of (regional) networks and platforms for farmers focusing on and encouraging an active exchange about the reduction of agricultural GHG emissions is an essential step towards achieving the ambitious goals that have been set. Basically, while it is not possible to oblige people to learn from others, it is important to create the right environment for social learning to take place (Rist et al. 2007). Farmers' overall mitigation knowledge could be improved if agricultural schools were to include climate change mitigation as a part of their general curriculum and extension agents included the topic regularly in their services.

Moreover, our findings suggest that promotion and support of regional (bottom-up) farmers' initiatives can be a useful tool for policymakers as it can generate behavioral change beyond the scope of the project itself. To this end, the goals and measures of these schemes should be communicated more widely so that others can learn by observing members' practices. In addition to the benefits relating to social learning promotion and potential spillover effects, collective action is particularly promising as an effective and efficient path towards agricultural climate change mitigation since it also has considerable cost and risk reduction potential (Bouamra-Mechemache and Zago 2015; Hodge and McNally 2000).

Our study also has implications for future research. Findings show that social networks, and especially contact to well-informed peers, play an important role in farmers' behavioral change. This implies that relational data of this kind should be collected more regularly and included in future research also beyond climate change mitigation, e.g., to explain farmers' adoption of agri-environmental measures. Particularly, more studies on the influence of relevant characteristics of network connections (instead of their mere existence) can contribute to deeper understanding of farmers' decision-making in response to their social environment. Additional data, e.g., on type of relationships or other sources of information, could also aid interpretation of results and help to explain network structures more thoroughly. Moreover, future research on the economic and ecological potential of farmers' collective action schemes is of particular relevance in the context of agricultural climate change mitigation.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10584-023-03484-6.

Acknowledgements The authors gratefully acknowledge the funding by the Swiss Federal Office for Agriculture and thank the Office of Landscape, Agriculture and Environment of Canton Zurich for providing census data for this research. Furthermore, the authors sincerely thank all farmers who participated in the interviews as well as in the previous online survey. We furthermore thank Jasmin Brunner, Vera Steiner, and Elisabeth Tanner for helping to conduct the interviews.

Author contribution Cordelia Kreft, conceptualization, data curation, formal analysis, writing—original draft; Mario Angst, conceptualization, methodology, data curation, formal analysis, writing—part of original draft, writing—review and editing; Robert Huber, conceptualization, writing—review and editing, supervision; Robert Finger, conceptualization, writing—review and editing, supervision

Funding Open access funding provided by Swiss Federal Institute of Technology Zurich

Data availability The data sets analyzed during the current study are available in the ETH research collection, https://www.research-collection.ethz.ch/handle/20.500.11850/458053.

Declarations

Competing interests The authors declare no competing interests.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

References

Adams J, Santos T, Williams VN (2021) Strategies for collecting social network data: overview, assessment and ethics. In: Light R, Moody J (eds) The Oxford Handbook of Social Networks. Oxford University Press

Agarwal, B., and Dorin, B. (2017). "Group farming in France. Why are some regions more conducive to cooperation than others?."

AgroCO2ncept (2016) AgroCO2ncept Flaachtal - Eine regionale Initiative für den Klimaschutz in der Landwirtschaft. In: Ressourcenprojekt AgroCO2ncept Flaachtal – Antrag. Verein AgroCO2ncept Flaachtal

Bamière L, David M, Vermont B (2013) Agri-environmental policies for biodiversity when the spatial pattern of the reserve matters. Ecological Economics 85:97–104

Bandiera O, Rasul I (2006) Social networks and technology adoption in northern Mozambique. The Economic Journal 116:869–902

Bernard T, Spielman DJ (2009) Reaching the rural poor through rural producer organizations? A study of agricultural marketing cooperatives in Ethiopia. Food Policy 34:60–69

BLW (2018). Ressourcenprogramm (B. f. L. B.-S. F. O. f. Agriculture, ed.).

Bodin Ö, Crona BI (2009) The role of social networks in natural resource governance: What relational patterns make a difference? Glob Environ Chang 19(3):366–374

Borgatti SP, Ofem B (2010) Social network theory and analysis. Soc net theory and educ change:17–29

Bouamra-Mechemache Z, Zago A (2015) Introduction: collective action in agriculture. Eur Rev Agric Econ 42:707–711

Brewer DD (2000) Forgetting in the recall-based elicitation of personal and social networks. Social Networks 22:29–43

Complex Data Collective (2016). Network canvas: software to simplify complex network data collection Vol. 7.

Conley TG, Udry CR (2010) Learning about a new technology: pineapple in Ghana. Am Econ Rev 100

Di Falco S, Doku A, Mahajan A (2020) Peer effects and the choice of adaptation strategies. Agric Econ 51:17–30

Dittrich D, Leenders RTA, Mulder J (2020) Network autocorrelation modeling: Bayesian techniques for estimating and testing multiple network autocorrelations. Sociol Methodol. 0081175020913899

Dupraz P, Latouche K, Turpin N (2009) Threshold effect and co-ordination of agri-environmental efforts. J Environ Plan Manag 52:613–630

Eddens, K. S., Fagan, J. M., and Collins, T. (2017). An interactive, mobile-based tool for personal social network data collection and visualization among a geographically isolated and socioeconomically disadvantaged population: early-stage feasibility study with qualitative user feedback. JMIR research protocols 6.

Fellmann T, Witzke P, Weiss F, Van Doorslaer B, Drabik D, Huck I, Salputra G, Jansson T, Leip A (2018) Major challenges of integrating agriculture into climate change mitigation policy frameworks. Mitig Adapt Strateg Glob Chang 23:451–468

Fitz-Koch S, Nordqvist M, Carter S, Hunter E (2018) Entrepreneurship in the agricultural sector: a literature review and future research opportunities. Entrep Theory Pract 42:129–166

Foster AD, Rosenzweig MR (1995) Learning by doing and learning from others: human capital and technical change in agriculture. J Polit Econ 103

Freeman LC (1979) Centrality in social networks conceptual clarification. Soc Netw 1

Granovetter M (1978) Threshold models of collective behavior. Am J Sociol 83:1420–1443

Hodge I, McNally S (2000) Wetland restoration, collective action and the role of water management institutions. Ecol E 35:107–118

Ingram J (2010) Technical and social dimensions of farmer learning: an analysis of the emergence of reduced tillage systems in England. J Sustain Agric 34:183–201

IPCC (2014). "Climate change 2014: mitigation of climate change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change ".

IPCC (2019). " Climate Change and Land, an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems.."

Isaac ME, Erickson BH, Quashie-Sam S, Timmer VR (2007) Transfer of knowledge on agroforestry management practices: the structure of farmer advice networks. Ecol Soc 12(2):32

Karrer, S. L. (2012). Swiss farmers' perception of and response to climate change, ETH Zurich, Diss No. 20410.

Keil A, D'souza A, McDonald A (2017) Zero-tillage is a proven technology for sustainable wheat intensification in the Eastern Indo-Gangetic Plains: what determines farmer awareness and adoption? Food Security 9:723–743
Kreft CS, Huber R, Wüpper DJ, Finger R (2020) Data on farmers' adoption of climate change mitigation measures, individual characteristics, risk attitudes and social influences in a region of Switzerland. Data in brief 30:105410
Kreft C, Huber R, Wuepper D, Finger R (2021a) The role of non-cognitive skills in farmers' adoption of climate change mitigation measures. Ecol Econ 189:107169
Kreft CS, Angst M, Huber R, Finger R (2021b) Social network data of Swiss farmers related to agricultural climate change mitigation. Data in Brief 35:106898
Krishnan P, Patnam M (2014) Neighbors and extension agents in Ethiopia: who matters more for technology adoption? J Agric Econ 96:308–327
Läpple D, Kelley H (2015) Spatial dependence in the adoption of organic drystock farming in Ireland. Eur Rev Agric Econ 42:315–337
Leenders RTA (2002) Modeling social influence through network autocorrelation: constructing the weight matrix. Soc net 24:21–47
Levy MA, Lubell MN (2017) Innovation, cooperation, and the structure of three regional sustainable agriculture networks in California. Reg Environ Chang 18:1235–1246
Manski CF (2000) Economic analysis of social interactions. J Econ Perspect 14:115–136
Mathijs E (2003) Social capital and farmers' willingness to adopt countryside stewardship schemes. Outlook on Agric 32:13–16
Matuschke I, Qaim M (2009) The impact of social networks on hybrid seed adoption in India. Agric Econ 40:493–505
Mills J, Gibbon D, Ingram J, Reed M, Short C, Dwyer J (2011) Organising collective action for effective environmental management and social learning in Wales. J Agric Educ Ext 17:69–83
Moschitz H, Roep D, Brunori G, Tisenkopfs T (2015) Learning and innovation networks for sustainable agriculture: processes of co-evolution, joint reflection and facilitation. Taylor & Francis
Munshi K (2004) Social learning in a heterogeneous population: technology diffusion in the Indian Green Revolution. J Dev Econ 73:185–213
Murendo C, Wollni M, De Brauw A, Mugabi N (2018) Social network effects on mobile money adoption in Uganda. J Dev Stud 54:327–342
OECD (2012) Farmer behaviour, agricultural management and climate change. Organisation for economic co-operation and development (OECD), Paris
OECD (2013). "Providing agri-environmental public goods through collective action."
Ornetzeder M (2001) Old technology and social innovations. Inside the Austrian success story on solar water heaters. Technol Anal Strateg Manag 13:105–115
Ornetzeder M, Rohracher H (2013) Of solar collectors, wind power, and car sharing: comparing and understanding successful cases of grassroots innovations. Glob Environ Change 23:856–867
Ostrom E (1990) Governing the commons: the evolution of institutions for collective action. Cambridge University Press, Cambridge
Perry BL, Pescosolido BA, Borgatti SP (2018) Egocentric network analysis: foundations, methods, and models. Cambridge University Press
Peres R (2014) The impact of network characteristics on the diffusion of innovations, Physica A: Statistical Mechanics and its Applications 402:330–343
Peter, S., Hartmann, M., Weber, M., Lehmann, B., and Hediger, W. (2009). THG 2020 – Möglichkeiten und Grenzen zur Vermeidung landwirtschaftlicher Treibhausgase in der Schweiz. IAW-Schriftenreihe 2009/1.
Prager K (2015) Agri-environmental collaboratives for landscape management in Europe. COSUST 12:59–66
Prager K, Reed M, Scott A (2012) Encouraging collaboration for the provision of ecosystem services at a landscape scale—rethinking agri-environmental payments. Land use policy 29:244–249
R Core Team (2021). A language and environment for statistical computing. R Foundation for Statistical Computing (Internet), Vienna, Austria. Lucent Technologies. https://www.R-project.org.
Richards, M., Bruun, T. B., Campbell, B. M., Gregersen, L. E., Huyer, S., Kuntze, V., Madsen, S. T., Oldvig, M. B., and Vasileiou, I. (2016). How countries plan to address agricultural adaptation and mitigation: an analysis of intended nationally determined contributions. CCAFS dataset.
Riley M, Sangster H, Smith H, Chiverrell R, Boyle J (2018) Will farmers work together for conservation? The potential limits of farmers' cooperation in agri-environment measures. Land Use Policy 70:635–646

Rist S, Chidambaranathan M, Escobar C, Wiesmann U, Zimmermann A (2007) Moving from sustainable management to sustainable governance of natural resources: the role of social learning processes in rural India, Bolivia and Mali. J Rural Stud 23:23–37

Schneider F, Fry P, Ledermann T, Rist S (2009) Social learning processes in Swiss soil protection—the 'from farmer-to farmer' project. Human ecology 37:475–489

Seyfang G, Smith A (2007) Grassroots innovations for sustainable development: towards a new research and policy agenda. Environmental politics 16:584–603

Skaalsveen K, Ingram J, Urquhart J (2020) The role of farmers' social networks in the implementation of no-till farming practices. Agricultural Systems 181:102824

Smith A, Seyfang G (2013) Constructing grassroots innovations for sustainability. Global Environmental Change 23:827–829

Smith P, Martino D, Cai Z, Gwary D, Janzen H, Kumar P, McCarl B, Ogle S, O'Mara F, Rice C, Scholes B, Sirotenko O, Howden M, McAllister T, Pan G, Romanenkov V, Schneider U, Towprayoon S (2007) Policy and technological constraints to implementation of greenhouse gas mitigation options in agriculture. Agric Ecosyst Environ 118:6–28

Smith P, Martino D, Cai Z, Gwary D, Janzen H, Kumar P, McCarl B, Ogle S, O'Mara F, Rice C (2008) Greenhouse gas mitigation in agriculture. Philos Trans R Soc 363:789–813

Stallman HR (2011) Ecosystem services in agriculture: determining suitability for provision by collective management. Ecological Economics 71:131–139

Šūmane S, Kunda I, Knickel K, Strauss A, Tisenkopfs T, Rios I, Rivera M, Chebach T, Ashkenazy A (2018) Local and farmers' knowledge matters! How integrating informal and formal knowledge enhances sustainable and resilient agriculture. J Rural Stud 59:232–241

Vaiknoras, K. A., Larochelle, C., and Alwang, J. (2020). The spillover effects of seed producer groups on non-member farmers in local communities in Nepal. In "2020 Annual Meeting, July 26-28, Kansas City, Missouri". Agricultural and Applied Economics Association.

van Dijk WFA, Lokhorst AM, Berendse F, de Snoo GR (2015) Collective agri-environment schemes: how can regional environmental cooperatives enhance farmers' intentions for agri-environment schemes? Land Use Policy 42:759–766

van Dijk WFA, Lokhorst AM, Berendse F, de Snoo GR (2016) Factors underlying farmers' intentions to perform unsubsidised agri-environmental measures. Land Use Policy 59:207–216

Vanni F (2013) Agriculture and public goods: the role of collective action. Springer Science & Business Media

Vroege W, Meraner M, Polman N, Storm H, Heijman W, Finger R (2020) Beyond the single farm–a spatial econometric analysis of spill-overs in farm diversification in the Netherlands. Land Use Policy 99:105019

Wollni M, Andersson C (2014) Spatial patterns of organic agriculture adoption: evidence from Honduras. Ecol Econ 97:120–128

Wuepper D, Sauer J, Kleemann L (2017) Sustainable intensification amongst Ghana's pineapple farmers: the complexity of an innovation determines the effectiveness of its training. Environ Dev Econ:1–22

Wuepper D, Zilberman D, Sauer J (2019) Non-cognitive skills and climate change adaptation: empirical evidence from Ghana's pineapple farmers. Clim Dev:1–12

Wreford A, Ignaciuk A, Gruère G (2017) Overcoming barriers to the adoption of climate-friendly practices in agriculture, OECD Food, Agriculture and Fisheries Papers, No.101, OECD Publishing

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.