Environment, Development and Sustainability
https://doi.org/10.1007/s10668-023-03729-5

Impacts of social capital on climate change adaptations of banana farmers in Southern China

Laurent Cishahayo[1] · Yueji Zhu[1] · Cheng Zhang[1] · Fang Wang[1]

Received: 18 May 2022 / Accepted: 30 July 2023

Abstract

Climate change has caused several significant risks to agro-economy in developing regions. Adaptations to climate change can improve farmers' resilience in agricultural production. Several studies revealed that farmers' adaptations are not based purely on farmers' individual competencies. This study attempts to contribute to the existing literature by exploring the relationship between social capital and farmers' climate change adaptations (CCA). We specified social capital into two components including social networks and training participation. Based on the primary data collected from 422 banana farmers in Southern China, poisson endogenous treatment effect model (PET) was used to estimate the effect of social capital on farmers' adoption intensity of CCA and examine the determinants of farmers' participation in social capital. The results reveal that social capital through both components significantly increased farmers' adoption intensity of CCA, highlighting the importance of social capital to boost farmers' intensity adoption of CCA in rural areas. Furthermore, education, political participation, land fertility, membership in farmer-based organizations, and income were significant incentives influencing farmers' participation in social capital. Policymakers are suggested to better understand farmers' adaptation decisions under weather variability and consider social capital in promoting adaptation strategies to enhance farmers' resilience in farming activities under climate change.

Keywords Social capital · Climate change adaptations · Adoption intensity · Training · Social networks · Banana farmers

1 Introduction

The recent extreme climate events around the world have reiterated the threat caused by climate change on agricultural production and food security that are essential for human being survival (IPCC, 2014). Existing study revealed that the adverse effects of climate change led to a global loss of 6.6% of GDP by the end of the twenty-first century (Takakura et al., 2019). In addition, the temperature is predicted to increase from 1.1 to 4.1 °C by

✉ Yueji Zhu
zhuyueji@126.com

[1] Department of Agri-Forestry Economics and Management, Management School, Hainan University, Haikou 570228, China

the 2060s (FAO, 2010). The unpredictable variation of rainfall, the rising temperature, and other climate hazards, including droughts and floods, may reduce crop yields and alter the existing cropping patterns of farmers (Boonwichai et al., 2019). Developing countries, whose economies are mostly relying on agriculture, are particularly affected by climate change and variability (Baidu et al., 2017; Owusu, 2016). Thus, climate change could pose tremendous risks to the livelihoods of smallholder farmers, particularly those with low adoption of farming techniques and inadequate technological advancement (Gupta et al., 2019; Omerkhil et al., 2020).

Banana is one of the leading crops in Southern China due to the favorable tropical conditions. However, banana production in Southern China has been recently challenged by climatic events such as extreme temperatures, droughts, and typhoons. Rising temperatures and droughts had a severe impact on banana production, making them more susceptible to diseases. Therefore, these hostile conditions lead to changes in growing conditions, resulting in a decrease in crop productivity (Ojo & Baiyegunhi, 2021). Banana growers are mostly affected because they are out of accurate adaptive measures to tackle the impacts of climate change. The inability of smallholders to adjust to irregular climatic events leads to low agricultural production; consequently, these farmers feel discouraged to combat the effects of climate variability. Therefore, it is essential to build the smallholder farmers' adaptive capacities to decrease the impacts of climate change, especially considering the prevailing challenges of banana productivity (Khan et al., 2020).

The factors determining farmers' adoption of specific technologies in agricultural production continue to attract research attention, while innovation in farming practices is not purely related to individual actions or competencies. The previous study argued various drivers of farmers' adoption of new technologies such as benefits from technology which is considered as a significant factor (Wossen et al., 2015), in which economic aspects, such as the price of crops and resources, accessibility to credit, and the availability of labor, are also considered among the most relevant factors (Abdulai & Huffman, 2014). In addition to economic variables, socio-economic factors including income, gender, age, and education as human capital can influence smallholder farmers' adoption of new technologies (Abdulai & Huffman, 2014; Esfandiari et al., 2020). Recent empirical work has also reported that farm characteristics such as land tenure stability, land fertility, farm size, types of crops, and livestock as proxies of physical capital significantly influence farmers' choices and usage of new agricultural techniques in Ghana (Zakaria et al., 2020). However, social capital has not received enough attention, especially in developing countries where social interactions of farmers are frequent and important ways to coordinate their decision-making, while adaptation to climate change is a dynamic social process, and is, therefore, influenced by farmers' socio-economic and intrinsic characteristics (Wolf, 2011). Besides economic incentives, social capital has a crucial role for rural farmers in making decisions (Antwi-Agyei et al., 2018; Juhola et al., 2016). Social capital was first introduced into social sciences by Coleman (1988). He defined social capital as a concept that may create the relations between actors/people or corporates that facilitate specific actions of actors within the social structure. However, there is still no common consensus over the meaning of social capital. There are many ways to identify and measure social capital. For example, certain studies defined social capital in the three main dimensions such as relational, structural, and cognitive social capital (Belay, 2020; Zainoddin et al., 2018). Other existing works divided social capital into bridging, linking, and bonding categories (Njuki et al., 2008; Teshome et al., 2016). Other scholars such as Miao et al. (2015) and Li et al. (2022) have specified social capital from the aspects of trust, social networks, cooperation, norms, and reciprocity. Also, it was acknowledged that various components of social capital may have a different influence on farmers' adoption of agricultural technologies (Wang et al., 2021). For example, recent existing works have stated that social capital via different components such as social networks, training, norms, and trust may enhance individual and collective adaptive measures (Alam et al., 2016; Aldrich et al., 2016). Hence, the present study followed the concept of Hunecke et al. (2017) and defined social capital as an effective method that may provide additional opportunities for farmers or groups of people to encourage them to work collaboratively, interact, participate in training, and invite them to use the potentialities from social networks. Therefore, social capital was measured into two components such as social networks and training.

Recently, the role of social capital of farmers in agricultural production has been discussed in many studies (Belay et al., 2019; Hao et al., 2020; Hunecke et al., 2017), and social capital is recognized as an important predictor of farmers' adoption of agricultural practices and innovations (Belay, 2020; Castillo et al., 2021; Yaméogo et al., 2018), particularly in the developing countries. For example, Alam et al. (2016) unveiled the positive impacts of social capital on farmers' adoption of early maturing varieties and crop diversification. Moreover, social capital was used as an effective tool that may enhance the adoption rate of improved technologies and management including land fertility techniques, soil and water conservation practices, and collective irrigation (Wossen et al., 2015). Furthermore, recent empirical work has unfolded the positive link between social capital and agricultural techniques in terms of different behaviors ranging from changes in fertilizer applications and product types to changes in marking approaches (Zhou et al., 2018). Likewise, the existing literature has pointed out how various alternative dimensions of social capital may influence farmers to take up crop management and post-harvest techniques (Belay & Fekadu, 2021). It was estimated that social capital through participation in training programs and social support positively influenced farmer's adoption of modern agricultural techniques in Kenya (Cofré-Bravo et al., 2019). Indeed, training acts as a social capital that connects farmers and enables them to engage strongly in their farming practices with their instructors and peers and can influence farmers' attitudes and behaviors through social norms established by agricultural cooperatives and helps them to simultaneously avoid maladaptation (Antwi-Agyei et al., 2018; Juhola et al., 2016). This would increase economic efficiency because it decreases costs and enhances adequate information, resulting in solving social problems (Priyanath & Lakshika, 2020). Further, social capital may increase farmers' adoption of CCA through capacity-building training participation (Zakaria et al., 2020). In fact, through social networks, social capital can diffuse formal or informal knowledge and skills among farmers and increase social interactions. For example, farmers who use social networks change their attitudes toward adaptations to climate change and increase their knowledge of the adaptive measures to mitigate the potential risks and chocks caused by weather variability (Saptutyningsih et al., 2020). As opined by Karanja Ng'ang'a et al. (2016), farmers' participation in social capital through social networks and training may enable farmers to change their farming practices and improve their livelihood by adopting new farming methods.

However, social capital does not inevitably have positive outcomes or serve as an insurance mechanism against negative risks and shocks. It may be inappropriate if there is a general lack of knowledge and resources to come up with efficient solutions. For example, previous empirical work in Ethiopia has unveiled that social capital could also hamper the adoption of CCA in rural areas (Paul et al., 2016). The credible explanation is related to the fact that many farmers who depend on community members are unlikely to try new agricultural technologies as individual households in Ethiopia. As stated by MacGillivray (2018), social capital through social networks may act as hindering factor to climate adaptations. This is attributed to the fact that strong social networks may act as channels for misperception, resulting in distorting farmers' decision-making and decreasing the incentives to adopt agricultural techniques (Zhou et al., 2018). Similarly, the existing literature has revealed that excessive social capital may lead to closed networks that limit access to extensive information; consequently, the farmers decrease the adoption rate of new technologies (Hunecke et al., 2017). It is also estimated that social capital may not be sufficient to prevail over the transaction costs of collective action (Paul et al., 2016). This was called the dark side of social capital, where the strong social institutions may provide negative outputs or overwhelm formal legal institutions as in the case of the mafia (Forkmann et al., 2022). Additionally, Kassie et al. (2015) unfolded that social capital via social networks may decrease the adoption rate of land management practices in Northern Ethiopia. This was because social networks may create a free rider challenge; therefore, farmers lose their incentives to acquire new ideas and information (Hunecke et al., 2017).

Thus, the present work contributes to existing studies in three ways. First, though the previous empirical works assessed the association between social capital and smallholder farmer's adoption of agricultural innovations, they usually focused on one innovative technology (Cofré-Bravo et al., 2019). The present study considers a group of adaptive measures to climate change and focuses more on how social capital affects farmers' intensity of CCA. Generally, farmers can adopt multiple adaptations in their agricultural practices, and the combination of these techniques can have a more robust impact on crop yields than a single one. For example, farm income could be increased by combining multiple agricultural technologies (Biru et al., 2020; Tambo & Mockshell, 2018). Moreover, the current work considers two components of social capital including social networks and agricultural training, because the existing evidence unfolded that the use of a single social capital component does not clearly explain the influence of various social capital components (Belay, 2020). Hence, the main objective of this work was to examine whether social capital influences smallholder farmers' adoption intensity of CCA in developing areas. Second, we explore the significant factors that influence farmer's decisions to participate in social capital through training and social networks. The stakeholders and agricultural extension workers need such information to develop policies to ensure that many farmers have accessibility to social capital to make the delivery of extension services faster and more cost-effective. Farmers may mobilize themselves into groups to increase their knowledge and skills, enabling them to diminish the harmful impacts of climate change, thereby improving their livelihoods. Third, the estimation of the impacts of social capital on adoption intensity of CCA may be biased using the simple regression model, because farmer's decision is self-selection instead of random selection. This study used Poisson endogenous treatment effect model (PET) which could address farmers' self-selection bias by taking into account the unobserved and observed factors to estimate the effects of farmers' social capital on the adoption intensity of CCA (count outcome). In doing so, the estimated results are robust and reliable (Danso-Abbeam et al., 2021).

The remainder of this work is arranged as follows. The following section describes the study area and data collection, while the estimation strategies are given in section three. The results and discussions are well explained in sections four and five, respectively. Finally, the conclusion and policy implications were presented in the last section.

2 Study area and data collection

This work was conducted in Southern China, specifically in Hainan Province. This part lies between longitudes 108° 37 and 111° 03' east longitude and latitude 18° 10' and 20°10' north latitude with an area of 34,000 km^2 (Domrös & Peng, 2012). The climate of Hainan Island is tropical, with monsoons predominant in April and October, north-easterly winds (November–March) in winter, and south-westerly winds typhoons (May–September) in summer. The mean rainfall is 1624 mm, and the mean temperature is ranged between 23 °C and 26 °C. In Hainan, the dry and rainy seasons are different. The dry season is warm and windy, and the rainy season is hot and humid.

Moreover, China is the second-largest country with high productivity of banana crops after India. Hainan is one of the main growing banana areas in China because it has a suitable area for growing banana crops since it is located in humid tropical climates; however, in recent years, the harvested area has dramatically shrunk and climate-related events such as typhoons, temperature rises, and droughts frequently occur; consequently, there is a remarkable decrease in banana productivity in the Hainan region (FAO, 2018). According to China's National Banana Industry Technology System (CNBITS), banana production was estimated at 1.53, 1.20, and 1.08 million tons in 2015, 2018, and 2020, respectively. Besides global warming, rising temperatures and droughts have caused severe impacts on banana production, making them more susceptible to diseases such as Panama disease and black Sigatoka. These factors can result in the loss of mass production during the harvest season, further discouraging farmers from growing bananas. As a result, diseases and climate-related stress pose an absolute challenge to farmers, given their poor adaptability and endless vulnerabilities. In this context, adaptation strategies are urgently needed, as climate change and variability can threaten banana yields, consequently undermining the sustainability of the banana industry in China.

This study uses the cross-sectional data collected from a field survey of banana growers in the Hainan Province of China from March to April 2021. We applied multi-stage sampling to choose the household farmers. First, Hainan Province was chosen because it is one of the main provinces where banana crops are mainly grown by smallholder farmers. In addition, banana crops are chosen because they are commonly produced in the Hainan Province. Second, four counties including Lingao, Chengmai, Ledong, and Changjiang were selected because they are leading banana-producing counties in Hainan Province. Third, we randomly selected three townships regarding the banana farm sizes, and two to five villages were chosen in each town. Then, 15–25 households were randomly selected in each village. Finally, we obtained 422 valid respondents of banana farmers. Samples were gathered through face-to-face interviews based on a structured questionnaire. Farmers were instructed about the aim of the study before the beginning of the questionnaire survey. They were aware that these samples would be only utilized for academic research purposes. For this reason, we promised that the privacy of farmers could not be infringed, and all sample was gathered and utilized based on their willful involvement. The sample distribution of the respondents is given in Table 1.

3 Estimation strategies

The present study followed the economic theory of household farmers engaged primarily in banana production while they can also allocate their time to participate in social capital. Therefore, the time allocation framework applied in this study was taken from the recent work of Danso-Abbeam and Baiyegunhi (2017). The concept of this framework is

Table 1 Sample distribution of the respondents

Counties	Respondents	Percentage (%)
Chengmai	100	23.60
Lingao	101	24.0
Changjiang	105	24.9
Ledong	116	27.5
Total	422	100

delivered from that farmers may enhance their utilities to a maximal extent by allocating their time into three major activities such as farming works, leisure, and farmers' participation in social capital (i.e., participation in agricultural training and social networks). Therefore, the household time constraint is expressed as $T = T_n + T_f + L$; where L and T_f represent leisure, and the time allocated to farming works, respectively, and T_n denotes participation in social capital into their two components (i.e., participation in social networks and training). In contrast, some farmers may not have access to social capital; consequently, the negative constraint was imposed on social capital such that $T_n \geq 0$.

In such observational studies, treatment choices are usually influenced by socio-economic characteristics because the subject factors of the treated group are not the same as those of the control group. Hence, to estimate the impacts of treatment on the outcome variable, one must consider the systematic differences between the two categories (control and treatment groups). Actually, farmer households may voluntarily decide to participate in social capital based on their demographic characteristics and productive resources, resulting in biased estimates. In such a case, the participation of farmers in social capital is not randomly assigned. Moreover, if farmer households are not randomly assigned to treatment, the decision of farmers to participate in social capital can be affected by unobserved and observed heterogeneities; consequently, the outcome variable of interest is also affected.

Moreover, another important econometric issue in impact assessment is the problem of missing data for counterfactual conditions. There are missing data because the outcome variables are only observable in one state at a time, but also the counterfactuals of each group cannot be noticed (Wooldridge, 2003). Several scholars relied on two major econometric frameworks including the propensity score approach and instrumental variables (IV) to address the problem of counterfactuals and the confounding variables (Danso-Abbeam & Baiyegunhi, 2019; Kassie et al., 2011). However, propensity score approaches such as regression adjustment, inverse probability weighting, and propensity score matching only consider the observed heterogeneities, whereas the IV method accounts for both unobserved and observed heterogeneities. Based on the various challenges above, the present study has employed Poisson regression with endogenous treatment model within the framework of IV. This model uses the count outcomes with the Poisson distribution of the error terms to analyze the impacts of social capital on the adoption intensity of adaptations to climate change.

Typically, participating in social capital is not an exogenous choice. Hence, it is considered as the endogenous binary treatment variable T_k and is influenced by farmers' socio-economic and intrinsic characteristics. In fact, T_k is endogenous when the treatment assignment is not random; consequently, some unobserved factors that affect T_k can also influence the outcome equation W_k. Since the adoption of adaptations to climate change is the count values $W_k = 0, 1, 2, 3, \ldots.., w_n$; and the farmers can decide to adopt some of them or not; hence, Q_k is defined as the second dummy, and it indicates the sample selection rule. This represents the farmer households who did not adopt any agricultural practices. In such a case,Q_k is missing for a certain proportion of the data, and the selection rule is defined when $Q_k = 1$ if the outcome variable (W_k) is observed, while $Q_k = 0$ when the outcome variable (W_k) is missing.

Following Miranda (2004), this study uses Poisson endogenous treatment effect model (PET) to solve the sample selection and endogeneity issues. This model takes into account the case where Q_k as a selection dummy is assigned the value 0 when the farmer did not adopt any adaptive measures (W_k is missing), and Q_k is assigned the value 1, if when the farmer has adopted some adaptive measures (W_k is observed).

Hence, endogenous treatment and the selection dummies are expressed according to the continuous latent variables as follows:

$$T_k^* = z'_{k\sigma} + \mu_k \tag{1}$$

$$Q_k^* = G'_K\beta + \delta T_k + \varepsilon_k \tag{2}$$

With $T_k = 1(T_k^* > 0);Q_k = 1(Q_k^* > 0)$.

Therefore, the outcome equation which follows the Poisson distribution is specified:

$$W_k = \left\{ \begin{array}{l} 0\ if\ Q = 0 \\ \left[\mu^{W_k} \exp(-\mu)\right]/W_k!\ if\ Q = 1 \end{array} \right\} \tag{3}$$

$$\text{Hence}, E(W_k/G_k, T_{k,}\varepsilon_k) = \exp\left(G_k\beta + \delta T_k + \varepsilon_k\right) \tag{4}$$

where G_k represents the vector of covariates used to estimate the count data, and Z_k represents the covariates for binary treatment. The error terms such as μ_k and ε_k are related to treatment and outcome equations, respectively, and are the bivariate normal distribution with zero 0 and the covariate matrix; hence, they are specified as follows:

$$\begin{bmatrix} \sigma^2 & \sigma\rho \\ \sigma\rho & 1 \end{bmatrix} \tag{5}$$

where G_k and Z_k are the exogenous covariates; therefore, the latter is not correlated to error terms. The conditional on ε_k and μ_k is normal with mean $\varepsilon_k\rho/\sigma$ and the variance (1-ρ^2). Furthermore, the PET model can estimate the average treatment effect on the treated (ATT). The latter is defined as the mean difference between the potential outcomes of the treated group and its counterfactual context (Cishahayo et al., 2022; Ma & Wang, 2020; Paudel et al., 2019; Teklewold et al., 2013). Employing the estimates of the PET estimator, ATT is expressed as given below:

$$ATT = E\left(W_{1k} - W_{0k}/T_k = 1\right) = E[E\{W_{1k} - W_{0k}/(Z_k, G_k), T_k = 1\}/T_k = 1] \tag{6}$$

where, hence,E(.) denotes the expectation operator, W_{1k} represents the potential outcome for farmers who have active participation in social capital, and W_{0k} indicates the potential outcomes of farmers in the counterfactual context.

Finally, this study has also employed augmented probability weighting regression adjustment (AIPW) and a doubly robust estimator to test the robustness of the estimated findings (Austin, 2011).

4 Results

4.1 Descriptive statistics of sample farmers

This section describes the core variables related to respondents. Farmers who participated in the social capital through training and social networks were 27% and 52%, respectively (Table 2). The high proportion of household farmers who participated in social capital could be related to the spillover effect. The active participation of household farmer's social capital may positively influence the intensity adoption of CCA and decrease the related chocks and damages caused by climatic events. The sample data were mainly dominated by male smallholder farmers (72%). The average farmers' age was estimated at 47 years old. It means that the majority of farmers were still young and productive. This could significantly affect farmers' uptake of adaptations to climate change as reported by Danso-Abbeam et al. (2021) that young smallholder farmers have a high propensity to adopt the new techniques as compared to old farmers. Moreover, most of the farmers (94%) have attained primary school. This implies that the respondents with access to social capital were mostly literate, resulting in the increase in farmers' likelihood to adopt CCA. The average farm size was 14.74 mu. That is, most of the farmers operate their agricultural activities on landholdings of less than one hectare; hence, they are more like smallholder farmers.

Furthermore, the average log income was recorded at 4.59 Yuan. Banana income may positively influence farmers' CCA because they are earning more benefits from banana production and are mainly engaged in agriculture. Moreover, 55% of respondents are members of FBOs in the study area. FBOs are an essential channel to connect farmers to output and input and link them to essential resources such as farmer field schools and other extension service. Approximately 45% of the farmers practiced irrigation. Irrigation offers important opportunities for farmers to enhance crops yields. It was reported that the farmers who adopted the irrigation method have high potentialities to improve 5.39–6.8% of rice yields in China (Zhuang et al., 2019). During the past 5 years, about 91% and 84% of the sampled farmers perceived climate change and droughts in their locality. This high perception of climate change and the frequency of droughts as threats to agricultural production can enhance the adoption of CCA because smallholder farmers have a high awareness of the risks and shocks caused by climatic events.

4.2 Farmers' adaptation strategies to climate change

Farmer households are inclined to use and adopt some adaptation measures to tackle the effects caused by weather variability and its related risks and damages (Abid et al., 2020). The adaptation measures include crop diversification, adjusting planting dates, drought-tolerant varieties, zero/minimum tillage, fallow, afforestation, soil improvement technology, and others. Therefore, farmers usually adopt the various adaptation measures according to their capabilities and needs, and CCA varies from farmer to farmer.

Several adaptation measures were considered by banana farmers, and the adoption intensity is ranged from 1 to 10 (Table 3). The value 1 is attributed to the respondent who adopted one adaptation strategy, while 0 indicates the farmers who did not adopt any adaptation. Therefore, due to the marginal disparities between the two categories (participants and non-participants in social capital), the pooled results were used in the discussion. Hence, among multiple CCA used by the banana farmers, crop diversification was mostly

Table 2 Summary of the descriptive statistics

Independent variables	Description	Mean	S.D
Social capital			
Participation in training	1 = if respondent usually takes part in training activity related to climate change adaptations; 0 = otherwise	0.27	0.45
Social networks	1 = if farmer often communicates with neighboring farmers about agricultural issues in production, 0 = otherwise	0.52	0.50
Socio-economic characteristics			
Age	Respondent's age (years)	47.13	11.03
Gender	1 = if respondent is a male; 0 = otherwise	0.72	0.44
Education	1 = if respondent has attended the formal school; 0 = otherwise	0.94	0.23
Household size	Number of the people in the family	5.36	1.95
Farming experience	Years engaged in farming activities	24.8	12.52
Labor force	Number of the person engaged in agriculture	2.60	1.28
Household asset			
Fertile soil	1 = if farmer perceived the low land fertility, 0 = otherwise	0.53	0.49
Farm size	Banana area cultivated (mu)	14.74	28.43
Land ownership	1 = farmer cultivated banana in his/her own land, 0 = otherwise	0.84	0.36
Irrigation status	1 = if the planting area has irrigation conditions, 0 = otherwise	0.45	0.49
Dist. to banana field	The distance from home to the banana field (km)	2.57	3.86
Market variables			
Ln income	The natural logarithm of total annual banana income (Yuan)	4.59	0 .52
Institutional variables			
Access to agricultural credit	1 = if farmer's households has accessed to agricultural credit; 0 = otherwise	0.40	0.49
FBOs membership	1 = if farmer's household is a member of the farmer-based organization (FBOs); 0 = otherwise	0.55	0.49
Political participation	1 = if farmer is a Communist Party member, 0 = otherwise	0.17	0.38
Climate variables			
Climate change perception	1 = if the farmer's households perceived climate change in their locality; 0 = otherwise	0.84	0.359
Drought frequency	1 = if farmer's households perceived drought during the past 5 years; 0 = otherwise	0.91	0.27

Table 2 (continued)

Independent variables	Description	Mean	S.D
Typhoon frequency	1 = if farmer's household perceived typhoons during the past 5 years; 0 = otherwise	0.82	0.38
Flood frequency	1 = if farmer's household perceived floods during the past 5 years, 0 = otherwise	0.37	0.48

1 mu = 1/15 ha

adopted among the respondents (76.30%) to reduce the impact of weather variability and its relevant damages. Our findings were in congruence with the study by Esfandiari et al. (2020) which revealed crop diversification as the most adopted strategy among farmers in Iran. The second most practiced CCA was adjusting planting date (51.1%), which again confirms the study of Zakaria et al. (2020) who reported that planting date adjustment is also one of the important adaptation strategies. In the study area, farmers realized that the variability of precipitation and temperature may be adapted by changing planting and harvesting dates.

Moreover, the disease and pest-resistant varieties were adopted by 50.1% of the farmers, while drought-tolerant and early maturing varieties were adopted by 40.9% and 42.4% of farmers, respectively. Early maturing varieties were used because of the irregular rainfall. Hence, these varieties shorten the planting season and are mostly used to reduce the total crop loss. Furthermore, the use of drought-tolerant crops and resistant to disease and pest varieties (hybrids) whose traits were improved for characteristics including drought resistance, high yields, pest and disease resistance, and quality improvement strategies dominate. The seeds with these properties are beneficial and valuable for farmers due to irregular precipitation and temperatures. Our results are also in line with those of Taruvinga et al. (2016) in South Africa, which reported that rain-dependent farmers use drought-resistant crop varieties to avoid a decrease in yield productivity. Additionally, higher temperatures and irregular precipitation introduce crop diseases and pests into the environment that have adverse effects on plant growth. Finally, afforestation and zero/minimum tillage were adopted by 35% and 28.9% of the respondents, respectively. It is evident that the increase in temperature can lead to poor soil retention and decreased land fertility (Biesbroek et al., 2013). In China, farmers also believed that the rising temperature makes the soil dry and kills some essential microorganisms in the soil. Hence, farmers adopted minimum tillage such as mulching and crop residues to decrease the soil moisture loss to wind and sunshine.

Additionally, the mean comparisons in Table 3 also showed that most of the adaptation measures were adopted by the participants in social capital compared to their counterparts. However, crop diversification and changing planting dates were mostly adopted

Table 3 Adoption levels of main adaptation strategies to climate change

Agricultural adaptation practices	Pooled Mean	Participants Mean	Non-participants Mean	Diff
No adaptations	0.0189	0.022	0.012	0.01
Crop diversification	0.763	0.745	0.792	-0.047
Adjusting planting dates	0.511	0.471	0.578	-0.107**
Disease and pest-resistant varieties	0.501	0.524	0.440	0.084**
Fallow	0.483	0.498	0.459	0.039
Early maturing varieties	0.424	0.429	0.415	0.014
Drought-tolerant varieties	0.409	0.460	0.327	0.133***
Afforestation	0.350	0.361	0.333	0.028
Zero/minimum tillage	0.289	0.330	0.220	0.11***
Soil improvement technology	0.315	0.418	0.144	0.274***
Intercropping	0.246	0.254	0.232	0.022

Participants represent farmers who have access to social capital, whereas the non-participants indicate those who do not have access to social capital by farmers who do not have access to social capital. It is estimated that these adaptation measures are considered as the conventional measures which did not require extra knowledge; hence, they are mainly adopted by the non-participants. Our findings were supported by Mwongera et al. (2017), who argued that smallholder farmers who have limited institutional access and less participation in the different agricultural training have less knowledge about the new adaptive measures, resulting in the adoption of traditional practices.

4.3 Adoption intensity of CCA

This section describes the adoption intensity of CCA among farmers in the study area (Table 4). Our results indicated that more than 98% of respondents took action to tackle the impacts of climate change. For example, farmer households that did not adopt any adaptation measure were about 1.89%, while 21.80% of the farmers adopted three adaptation practices. Furthermore, the majority of farmers (73%) have taken three to six adaptation actions to decrease the risks and shocks associated with climate events.

Furthermore, the mean adoption intensity of CCA is 4.37 with a standard deviation of 1.71. That is, the average farmer had employed about four CCA to increase agricultural productivity under weather variability. The adoption of several adaptation measures was expected because some of them complete each other in their effectiveness (Zakaria et al., 2020). Furthermore, the mean comparison also indicated that the farmer households with active participation in social capital have high likelihoods to adopt and use multiple adaptation techniques as compared to the non-participants (Table 4).

4.4 Effects of social capital on farmers' adoption intensity of CCA

The outputs from the PET model are shown in Tables 5 and 6. The *P*-values related to Wald Chi^2 indicate that the models are well-fitted and are positively significant at the 1% level. The Wald independence test values ($\rho = 0$) (67.19, $p > 0.0000$) and (124.80, $p > 0.0000$) indicate a denial of the null hypothesis of no correlations between social

Table 4 Adoption intensity of CCA

Adoption intensity	Pooled sample		Participants		Non-participants	
	Frequency	%	Frequency	%	Frequency	%
0	8	1.89	6	2.28	2	1.25
1	17	4.02	6	2.28	11	6.92
2	40	9.47	20	7.60	20	12.58
3	92	21.80	54	20.53	38	23.89
4	81	19.80	47	17.87	34	21.38
5	70	16.58	52	19.77	18	11.32
6	61	14.45	41	15.59	20	12.57
7	36	8.53	24	9.12	12	7.54
8	11	2.60	7	2.66	4	2.51
9	4	0.98	4	1.52	0	0
10	2	0.47	2	0.76	0	0

Farmers may select various adaptation choices; N = 422 farmers capital in the two components (social networks and agricultural training) and the error term. Moreover, the significance of rho (ρ) also means that the unobservable factors of the farming household that affects farmer's decisions to engage in social capital also influence the adaptations to climate change. Therefore, the use of PET is appropriate to solve the endogeneity problem.

Table 5 Estimated effect of social capital through training participation on farmers' adoption intensity of CCA

Variables	Training		Adoption intensity of CCA	
	Coefficient	S.E	Coefficient	S.E
Social capital				
Training		–	0.1568***	0.045
Socio-economic characteristics				
Age	0.0209	0.011	−0.0059*	0.0033
Gender	0.117	0.181	0.074	0.055
Education	0.767*	0.422	0.1001	0.102
Farming experience	−0.0115	0.009	0.00031	0.0029
Household size	−0.006	0.044	0.0148	0.013
Labor	−0.0331	0.070	−0.012	0.018
Household asset				
Farm size	0.003	0.003	−0.00017	0.0008
Land ownership	−0.255	0.199	0. 255***	0.068
Land fertility	0.169	0.146	0.276	0.041
Irrigation status	−0.189**	0.142	0.0299	0.04
Dist. to banana field	−0.028*	0.022	−0.0066*	0.005
Market variables				
Ln income	−0.102	0.168	0.024	0.047
Institutional variables				
Member of FBOs	0.352**	0.145	0.0357	0.041
Political participation	0.332**	0.179	−0.047	0.0547
Agricultural credit	0.116	0.143	−0.0067	0.041
Climate variables				
Climate change perception	0.129	0.210	0.117**	0.063
Drought frequency	0.095	0.256	0.236***	0.613
Typhoon frequency	−0.35	0.177	0.059	0.045
Flood frequency	−0.234	0.147	0.064	0.0415
Constant	−1.787**	1.04	1.177***	0.299
Rho (ρ)	–	−1.403***	0.17	
Sigma (σ)	–	−6.146***	1.39	
Log-likelihood	−227.83	−1087.75		
Wald Chi-square	–	71.07, Prob > Chi 2 = 0.000		
Wald test of independent equations ($\rho = 0$)	–	67.19, Prob > Chi2 = 0.000		
Observation	422			

*, **, and *** indicate 10, 5, and 1 percent statistical significance levels, respectively

Table 6 Estimated effect of social capital through the social network on farmers' adoption intensity of CCA

Variables	Social networks		Adoption intensity of CCA	
	Coefficient	S.E	Coefficient	S.E
Social capital				
Social networks	–	0.106**	0.044	
Socio-economic characteristics				
Age	0.013	0.010	−0.005*	0.003
Gender	0.191	0.168	0.065	0.054
Education	1.718***	0.528	0.084	0.103
Farming experience	−0.012	0.009	0.00007	0.002
Political participation	0.152	0.182	−0.033	0. 056
Household size	0.045	0.042	0.0128	0.013
Labor	−0.063	0.066	−0.012	0.018
Household asset				
Farm size	0.0043	0.004	−0.00011	0.0007
Land ownership	−0.130	0.20	0.244***	0.069
Land fertility	0.332**	0.140	0.025	0.042
Irrigation status	−0.386**	0.136	0.032	0.041
Dist. to banana field	0.025	0.026	−0.0078*	0.005
Market variables				
Ln income	0.341*	0.170	0.118	0.044
Institutional variables				
Member of FBOs	0.217**	0.137	0.043	0.042
Political participation	0.115	0.182	−0.034	0.056
Agricultural credit	0.13	0.14	−0.005	0.04
Climate variables				
Climate change perception	0.160	0.194	0.120**	0.062
Drought frequency	−0.266	0.249	0.224***	0.063
Typhoon frequency	0.166	0.177	0.038	0.046
Flood frequency	0.052	0.14	0.0528	0.041
Constant	−3.96***	1.109	1.228***	0.296
Rho (ρ)	–	−1.48***	0.132	
Sigma (σ)	–	−5.091***	0.583	
Wald Chi^2	–	63.08, Prob > Chi2 = 0.0000		
Wald test of independent equations ($\rho = 0$)	–	124.8, Prob > Chi2 = 0.0000		
Log-likelihood	−250.82	−1117.487		
Observation	422			

*, **, and *** indicate 10, 5, and 1 percent statistical significance levels, respectively

The estimated results of factors influencing farmers' participation in social capital are reported in column 2 of Tables 5 and 6, respectively. Hence, it is estimated that social capital is an effective tool to disseminate new farming technologies for farmers; therefore, it is essential to understand the factors that may influence farmers to take part in social capital so that these factors may guide policymakers to invest in social capital. As shown in column 2 of Tables 5 and 6, we depicted the factors that may influence farmer households to take part in the social capital via agricultural training and social network. The estimated result revealed that membership in FBOs is significantly and positively associated with farmers' participation in social capital through social networks and training at 5% level of significance. This enhances the active participation in social capital via social networks and trainings compared to their counterparts. Additionally, the findings of this study indicated that education had a positive and statistically significant relationship with social capital via both components at 5% level of significance. This means that farmers' education may enhance their involvement in social capital. Furthermore, as compared to their counterparts, farmers' income and land fertility significantly and positively influenced their participation in social capital via social networks at 10% and 5% levels of significance, respectively (column 2 of Table 6). Additionally, participation in the political party had a positive effect and was statistically significant on farmers' involvement in social capital through training at 5% level of significance as shown by its positive sign (column 2 in Table 5). That is, farmers who are willing to take part in a political party are likely to engage in social capital compared to their counterparts. Lastly, distance from farmers' residence to banana lands had a positive influence and was statistically significant on farmers' participation in social capital through training (column 2 in Table 5). However, the irrigation status is significantly and negatively associated with farmers' social capital through social networks and trainings at 5% level of significance as indicated by its negative sign, suggesting that the availability of water for irrigation decreases farmers' propensity to engage in the social capital compared to their counterparts since those farmers may easily tackle the climate change impacts.

The estimated effects of social capital on farmers' intensity adoption of CCA were reported in column 4 of Tables 5 and 6, respectively. The results show that social capital had positively and significantly affected farmer's adoption intensity of CCA through both components, including participation in social networks and training at 5% and 1% levels of significance, respectively. This implies that farmers who are actively involved in social capital through social networks or agricultural training were more likely to take up more adaptive measures against climate change in banana cultivation. Furthermore, farmers' perception of climate change and drought frequency significantly and positively increases their adoption intensity of CCA at 5% and 1% levels, respectively, compared to their counterparts. The households with land ownership had a positive and statistically significant on the adoption intensity of CCA at 1% level, suggesting that the farmers who own their farms are significantly more likely to adopt many CCA so that they may decrease the negative events of climatic changes. However, distance from farmers' residences to the banana field and respondents' age negatively influenced the adoption intensity of CCA of farmers at 10% level of significance. This indicates that the longer distance from households' residence decreases farmers' intensity of CCA, while the older farmers are less likely to take up multiple adaptive measures to tackle the climate change impacts than the younger.

4.5 Robustness check

The main objective of this work was to examine the causal effects of social capital on the adoption intensity of CCA. Descriptive statistics were employed to compare the mean average of adaptive techniques used by the participants and non-participants in social capital (Table 3). It showed that farmer households who are engaged in social capital have a high adoption of adaptive measures than non-participants. However, the differences in average adaptive techniques between the two groups may be misleading since the comparison failed to take into account the potential difference in subject characteristics between them. The PET model used in this study considers the endogeneity problem but the direct coefficient from the model cannot be taken as ATT. To solve this issue, we calculate the effects of social capital on farmers' adoption intensity of CCA using ATT and employ AIPW to test the robustness of the estimated results. As shown in Table 7, the conditional treatment effects which estimated ATT of farmer's participation in social capital through both components (i.e., participation in training and social network) on adoption intensity of CCA are approximately 4.076 and 4.071, respectively, and statistically significant at 1% level. This implies that farmers engaged in social capital adopted about four more CCA than their counterparts.

Consistent with the findings from the PET model, AIPW shows considerable gains in the increase in adoption intensity of CCA that result from participation in social capital. The AIPW test indicates that the ATT results were approximately 4.067 and 4.057 for social capital through participation in agricultural training and social networks, respectively, suggesting that the participants in social capital adopted four more adaptation strategies than non-participants. The results from the two methods confirm that farmer households with active participation in social capital could positively enhance the use of multiple adaptive techniques to decrease the adverse impacts of climate change.

5 Discussion

5.1 Impact of social capital on farmers' adoption intensity of CCA

Our findings provide an elaborated perspective to understand the causal effect of social capital via two components on farmers' adoption intensity of CCA. Sustainable agriculture can be achieved when farmers have adopted practices to neutralize climate change impacts in agricultural production (Kassie et al., 2015; Manda et al., 2016; Teklewold et al., 2013). However, many farmers from developing areas are less educated; consequently, they are mainly relying on the knowledge/skills and information obtained from their social networks to make decisions in farming activities (Cishahayo et al., 2022; Shikuku, 2019; Tripathi & Mishra, 2017). Thus, this current study primarily sought to investigate the link between farmers' social capital and the adoption intensity of CCA in the case of banana cultivation. Our findings indicated that social capital through both components (i.e., social networks

Table 7 Average treatment effect of social capital on adoption intensity of CCA

Treatment effects	Social networks		Training	
	Coefficient	S.E	Coefficient	S.E
Poisson regression with endogenous treatment effect				
ATT	4.076***	0.174	4.071***	0.128
Augmented inverse probability weighted regression adjustment (AIPW)				
ATT	4.057***	0.190	4.067***	0.125

*, **, and *** indicate 10, 5, and 1 percent statistical significance levels, respectively

and agricultural training) had positively and significantly influenced farmer's adoption intensity of CCA. It means that farmer households who have access to social capital have high probabilities to increase their knowledge regarding the adoption intensity of CCA in farming production. Our results were supported by the work of Saptutyningsih et al. (2020), who unveiled that participation in the social capital may play a considerable role in the adaptation process against climatic changes in Indonesia. Similarly, social capital can improve farmers' livelihoods by changing agricultural practices especially when farmers need to adopt new farming methods and agricultural innovations (Cofré-Bravo et al., 2019). As opined by Zeweld et al. (2017), farmers who have access to social capital may change their attitudes and behaviors regarding the adoption of new agricultural techniques. Furthermore, we checked the robustness of our findings using AIPW. Hence, the estimates from the two estimation methods are consistent and unveiled that participants in social capital via social networks and training may adopt four more adaptations than non-participants (Table 7). What the current study findings suggest and add up to the existing literature is that farmers with active participation in social capital can enhance farmer's propensity to adopt many adaptive measures compared to non-participants. The use of social capital can enhance farmers' knowledge/skills related to agricultural production; hence, they are inclined to take more CCA. Our findings emphasize the positive role of social capital in helping farmers gain confidence and experience in CCA adoption strategies.

In terms of control variables, the frequency of drought and climate change perception had a significant association with farmer households' adoption intensity of CCA. That is, the increase in adaptation was mostly influenced by the increase in the high perception of climate change and droughts. Therefore, farmers who believe that weather variability has a negative effect on their crops have a high propensity to adopt many adaptive techniques to combat the adverse impacts of climate change (Aryal et al., 2020; Esham & Garforth, 2013; Kibue et al., 2016). However, smallholder farmers who denied the climate change damages and exhibited wishful thinking have a low probability to enhance their adaptation techniques (Le Dang et al., 2014). In addition, farmers who experienced droughts in the past 5 years have taken several adaptive techniques to mitigate the impacts of climate change. This is in accordance with Danso-Abbeam et al. (2021) in Ghana. Moreover, it is expected farmers' age significantly influences the adoption intensity of CCA in that the farmers with advanced ages are more experienced in agricultural activities compared to the younger farmers. In contrast, our findings indicated that farmers' age was negatively signed and had a significant impact on the intensity adoption of adaptations to climate change. It means that adaptation strategies decrease with farmers' age. It is related to the fact that the old farmers have a high-risk aversion; consequently, they are unlikely to adopt multiple adaptive measures, while the younger farmers have a high probability of taking risks related to new agricultural innovations. Our findings were supported by Ahmad et al. (2021), who argued that older farmers are averse to the adoption of CCA because they are accustomed to their traditional practices, and are reluctant to change their farming behavior; consequently, they hesitate to apply modern agricultural techniques.

Furthermore, the result on land ownership was positive and statistically significant on smallholder farmer's adoption intensity of CCA. It implied that as the farmers had their lands, they have a high likelihood of adopting various adaptive techniques. Indeed, it is easy for farmers to decide on adaptive measures when the farmers own the land. Our findings were supported by Ehiakpor et al. (2021) in Ghana, who revealed that farmers who grew maize on their farms have a high probability to practice various adaptations to climate change, including crop rotation and changing planting dates. Similarly, Ahmad et al. (2021) also reported that the farmers who grow crops on their farmlands are more likely to adopt crop diversification and drought-tolerant crop varieties. However, the study revealed a negative association between the distance from farmers' residence to the banana land and the intensity of CCA uptake (column 4 in Table 6). It implies that the farmers who traveled long distances to reach their banana plots had significantly low adoption intensity of CCA. Thus, longer distances to banana plots may reduce farmers' adoption of CCA intensity in many ways. In particular, the longer distances decrease farmers' contact hours with their farming activities. Consequently, the cumulative effects of inadequate access to banana plantations reduce the uptake of CCA and reduce agricultural productivity. This supports the work by Ehiakpor et al. (2021) in Ghana, who pointed out that smallholder farmers from long distances to their maize plots are unlikely to take action against climate change, including crop residue retention and crop rotation.

5.2 Determinants of farmers' participation in social capital

Among the determinants of farmers' social capital, the FBOs were found to have statistically and positively affected farmers' probability to participate in social capital. It indicates that smallholder farmers who took part in the farming groups are likely to participate in social capital compared to non-participants. According to Zakaria et al. (2020), the FBOs may be used as an instrument to encourage the adoption intensity of adaptations to climate events through training in Ghana. Additionally, FBOs may encourage farmers to participate in social capital. Similarly, Ehiakpor et al. (2021) reported that farmers engaged in farming groups have a high opportunity to teach one another modern methods to mitigate climate change impacts. Moreover, participation in political activities had a positive impact on farmers' access to social capital through training. It implies that the leaders may identify the common issues and alert them in the political meetings at the village level; they may also advocate farmers to take part in social capital so that they may improve their skills and knowledge, which will help them to solve these common issues. Cooperation between farmers is very important as it enhances collection actions, which helps them to increase the adaptive capacity of farm households (Abid et al., 2016). Our results agreed with Biesbroek and Candel (2020), who reported that political participation enhances farmers' likelihood to make changes in agricultural practices.

Furthermore, households with certain education attainment have a high tendency to take part in social capital through social networks, as indicated by positive and significant estimates of educational variable (column 2 in Table 6). It is quite understandable given the importance of education in increasing farmers' knowledge/skills required to adopt new technologies, including adaptations to climate change. It can also be an instrument to equip with better skills and develop a positive attitude to use better adaptive measures to climate change. Our results were consistent with those of Challa and Tilahun (2014). In addition, the study reveals that farmers who perceived the low land fertility in the banana plot have a high probability to get involved in social capital via social networks, as indicated by the significant estimate (column 2 of Table 6). Thus, they are willing to participate in social capital and interact with other farmers to seek information on how they could restore land fertility for increasing farm productivity. Ehiakpor et al. (2021) reported similar results in Ghana. High income from banana crops had a positive association with farmers' participation in social capital through training (column 2 of Table 6). It implies that income has a vital role in determining a farmer's resilience. High banana income encourages farmers to participate in social capital and easily adopt more adaptive measures, including crop diversification and adjusting the farming calendar (Duffy et al., 2021). The increase in farm income enhances farmers' likelihood to invest in farming activities for high expected profitability via the adoption of CCA. Our findings are similar to the previous evidence of Esfandiari et al. (2020).

However, the distance to banana lands had a negative relationship with social capital through training. It implies that farmers who traveled long distances to reach their banana lands had a low probability to participate in social capital; consequently, they are unlikely to adopt many adaptation measures. Our findings were in congruence with Ehiakpor et al. (2021) in Ghana which revealed that the longer distance between farmers' residence and maize plots decreases the likelihood of participation in the social capital through climate change capacity-building training; consequently, they are unlikely to decrease the impacts of climatic events. Finally, irrigation status has adversely affected participation in social capital through training and social networks. Forty-five percent of farmers had access to irrigation on banana plantations in the study area. That is, farmers who efficiently operate the irrigation have a low likelihood to take part in the social capital through participation in agricultural training and social network; consequently, they are less likely to use adaptive measures. Our results are in the same line with Zakaria et al. (2020), who acknowledged that easy access to irrigation for year-round production decreases farmers' likelihood to actively seek information on CCA.

6 Conclusion

The dissemination of adaptive strategies to smallholder farmers is a crucial strategy to decrease the adverse effects of climate change and promote sustainable farming practices in developing countries. This study aims to investigate the effect of social capital on farmer's adoption intensity of CCA and specify the determinants of farmer's active participation in social capital. Hence, the present study can provide three main findings. First, we find that social capital (participation in training and social network) exerts a positive and significant impact on farmers' adoption intensity of CCA. Specifically, our estimates unveiled that social capital significantly increased farmer's propensity to use more than four climate change techniques than farmers who did not participate in social capital. The present work highlights the importance of social capital on farmers' adaptive response to climate change in agricultural production in developing areas. Second, other variables such as land ownership, climate change perception, and drought frequency were significant incentives for improving farmers' adoption of CCA strategies. This study also revealed that crops diversification, disease and pest-resistant varieties, and planting date adjustments are the most used strategies to adapt to climate change in Southern China, particularly for small-scale farms. Third, participation in social capital is heterogeneous among farmers. Specifically, farmers' participation in social capital was positively influenced by land fertility and banana income. Moreover, political participation, FBOs, and education have an essential role in determining farmers' participation in social capital. Membership in farming groups or political parties increases the accessibility to social capital and enhances farmers' adoption of CCA strategies in rural areas.

7 Recommendations and future work

Given the current high vulnerability among farmers in developing areas, the following policy implications are imperative to enhance farmers' resilience against climatic changes in farming practices. First, extension agencies could take advantage of farmer's active participation in social capital to develop new farming technologies in developing regions, where social capital is embedded in the rural communities. Additionally, policymakers and NGOs could facilitate the extension agencies to spread information regarding new technologies via social capital as well as investment in social capital participation. For example, that investment could be used to provide the training and making a demonstration of innovations to help farmers from developing regions. Second, the exchange mechanism and regular communication could be established between smallholder farmers and public extension agencies using social capital to provide a good understanding of the adoption intensity of CCA. Social capital is an effective way to diffuse the new agricultural techniques for farmers who are even illiterates. NGOs and policymakers could also motivate the trained and educated farmers to promote the dissemination of innovations to farmers through social capital. Third, incentive measures for farmers should be designed to encourage the adoption of CCA and sustain food security.

In spite of the significance of the study findings, there may be underlying limitations. First, we have considered two components of social capital. In contrast, future studies may consider other social capital components, such as trust and other ways of skill diffusion. It is expected that farmers' trust and learning from other farmers and agricultural technicians are expected to improve their skills and lead to active management of agricultural practices. Second, the analysis focuses more on smallholder farmers in developing regions, and hence, the findings should be applied to large-scale farms with caution. This is because there exist inherently different needs for social capital across different groups of farmers. Third, the present study has employed cross-sectional data, while the effectiveness of farmer households' social capital on the intensity of climate change adoption strategies can be observable after a certain period. Therefore, future research would be carried out using panel datasets.

Funding This research received funding from the National Natural Science Foundation of China (No. 71863006); Hainan Province Natural Science Foundation of China (No. 720RC581); the Philosophy and Social Science Major Program administered by the Education Department of Henan Province (No. 2022-YYZD-14); China Agriculture Research System of MOF and MARA (No. CARS-31).

Data availability The datasets analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of 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.

References

Abdulai, A., & Huffman, W. (2014). The adoption and impact of soil and water conservation technology: An endogenous switching regression application. *Land Economics, 90*(1), 26–43.

Abid, M., Ali, A., Raza, M., & Mehdi, M. (2020). Ex-ante and ex-post coping strategies for climatic shocks and adaptation determinants in rural Malawi. *Climate Risk Management, 27*, 100200.

Abid, M., Schilling, J., Scheffran, J., & Zulfiqar, F. (2016). Climate change vulnerability, adaptation and risk perceptions at farm level in Punjab, Pakistan. *Science of the Total Environment, 547*, 447–460.

Ahmad, D., Afzal, M., & Rauf, A. (2021). Farmers' adaptation decisions to landslides and flash floods in the mountainous region of Khyber Pakhtunkhwa of Pakistan. *Environment, Development and Sustainability, 23*(6), 8573–8600.

Alam, G. M., Alam, K., & Mushtaq, S. (2016). Influence of institutional access and social capital on adaptation decision: Empirical evidence from hazard-prone rural households in Bangladesh. *Ecological Economics, 130*, 243–251.

Aldrich, D. P., Page-Tan, C. M., & Paul, C. J. (2016). *Social capital and climate change adaptation*. Oxford Research Encyclopedia of Climate Science.

Antwi-Agyei, P., Dougill, A. J., Stringer, L. C., & Codjoe, S. N. A. (2018). Adaptation opportunities and maladaptive outcomes in climate vulnerability hotspots of northern Ghana. *Climate Risk Management, 19*, 83–93.

Aryal, J. P., Sapkota, T. B., Rahut, D. B., Krupnik, T. J., Shahrin, S., Jat, M. L., & Stirling, C. M. (2020). Major climate risks and adaptation strategies of smallholder farmers in coastal Bangladesh. *Environmental Management, 66*(1), 105.

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research, 46*(3), 399–424.

Baidu, M., Amekudzi, L. K., Aryee, J. N., & Annor, T. (2017). Assessment of long-term spatio-temporal rainfall variability over Ghana using wavelet analysis. *Climate, 5*(2), 30.

Belay, D. (2020). Determinants of individual social capital in dairy cooperatives in West Shoa, Ethiopia. *Agrekon, 59*(3), 303–320.

Belay, D., & Fekadu, G. (2021). Influence of social capital in adopting climate change adaptation strategies: Empirical evidence from rural areas of Ambo district in Ethiopia. *Climate and Development, 13*(10), 857–868.

Belay, D., Negatu, W., & Ayele, S. (2019). Gender, social capital, and market participation in dairy cooperatives in West Shoa, Ethiopia. *Journal of Gender, Agriculture and Food Security Agri-Gender, 4*, 25–41.

Biesbroek, G. R., Klostermann, J. E., Termeer, C. J., & Kabat, P. (2013). On the nature of barriers to climate change adaptation. *Regional Environmental Change, 13*(5), 1119–1129.

Biesbroek, R., & Candel, J. J. (2020). Mechanisms for policy (dis) integration: Explaining food policy and climate change adaptation policy in the Netherlands. *Policy Sciences, 53*(1), 61–84.

Biru, W. D., Zeller, M., & Loos, T. K. (2020). The impact of agricultural technologies on poverty and vulnerability of smallholders in Ethiopia: A panel data analysis. *Social Indicators Research, 147*(2), 517–544.

Boonwichai, S., Shrestha, S., Babel, M. S., Weesakul, S., & Datta, A. (2019). Evaluation of climate change impacts and adaptation strategies on rainfed rice production in Songkhram River Basin, Thailand. *Science of the Total Environment, 652*, 189–201.

Castillo, G. M. L., Engler, A., & Wollni, M. (2021). Planned behavior and social capital: Understanding farmers' behavior toward pressurized irrigation technologies. *Agricultural Water Management, 243*, 106524.

Challa, M., & Tilahun, U. (2014). Determinants and impacts of modern agricultural technology adoption in west Wollega: The case of Gulliso district. *Journal of Biology, Agriculture and Healthcare, 4*(20), 63–77.

Cishahayo, L., Yang, Q., Zhu, Y., & Wang, F. (2022). Learning behavior, environmental awareness, and agricultural waste management of banana farmers in China. *Social Behavior and Personality: An International Journal, 50*(5), 1–11.

Cofré-Bravo, G., Klerkx, L., & Engler, A. (2019). Combinations of bonding, bridging, and linking social capital for farm innovation: How farmers configure different support networks. *Journal of Rural Studies, 69*, 53–64.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology, 94*, S95–S120.

Danso-Abbeam, G., & Baiyegunhi, L. J. (2017). Adoption of agrochemical management practices among smallholder cocoa farmers in Ghana. *African Journal of Science, Technology, Innovation and Development, 9*(6), 717–728.

Danso-Abbeam, G., & Baiyegunhi, L. J. (2019). Does fertiliser use improve household welfare? Evidence from Ghana's cocoa industry. *Development in Practice, 29*(2), 170–182.

Danso-Abbeam, G., Ojo, T. O., Baiyegunhi, L. J., & Ogundeji, A. A. (2021). Climate change adaptation strategies by smallholder farmers in Nigeria: Does non-farm employment play any role? *Heliyon, 7*(6), e07162.

Domrös, M., & Peng, G. (2012). *The climate of China*. Springer Science & Business Media.

Duffy, C., Pede, V., Toth, G., Kilcline, K., O'Donoghue, C., Ryan, M., & Spillane, C. (2021). Drivers of household and agricultural adaptation to climate change in Vietnam. *Climate and Development, 13*(3), 242–255.

Ehiakpor, D. S., Danso-Abbeam, G., & Mubashiru, Y. (2021). Adoption of interrelated sustainable agricultural practices among smallholder farmers in Ghana. *Land Use Policy, 101*, 105142.

Esfandiari, M., Khalilabad, H. R. M., Boshrabadi, H. M., & Mehrjerdi, M. R. Z. (2020). Factors influencing the use of adaptation strategies to climate change in paddy lands of Kamfiruz. *Iran. Land Use Policy, 95*, 104628.

Esham, M., & Garforth, C. (2013). Agricultural adaptation to climate change: Insights from a farming community in Sri Lanka. *Mitigation and Adaptation Strategies for Global Change, 18*(5), 535–549.

FAO. (2010). *Climate-smart agriculture: Policies, practices and financing for food security*. UN Food and Agriculture Organization (FAO): Adaptation and Mitigation.

FAO. (2018). *FAOSTAT Database*. UN Food and Agriculture Organization (FAO). https://www.fao.org/faostat

Forkmann, S., Webb, J., Henneberg, S. C., & Scheer, L. K. (2022). Boundary spanner corruption: A potential dark side of multi-level trust in marketing relationships. *Journal of the Academy of Marketing Science, 50*(5), 889–914.

Gupta, A. K., Negi, M., Nandy, S., Alatalo, J. M., Singh, V., & Pandey, R. (2019). Assessing the vulnerability of socio-environmental systems to climate change along an altitude gradient in the Indian Himalayas. *Ecological Indicators, 106*, 105512.

Hao, F., Liu, X., & Michaels, J. L. (2020). Social Capital, carbon dependency, and public response to climate change in 22 European countries. *Environmental Science & Policy, 114*, 64–72.

Hunecke, C., Engler, A., Jara-Rojas, R., & Poortvliet, P. M. (2017). Understanding the role of social capital in adoption decisions: An application to irrigation technology. *Agricultural Systems, 153*, 221–231.

IPCC. (2014). Summary for Policymakers. In *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. United Kingdom and New York, NY: USA. Cambridge University Press, Cambridge.

Juhola, S., Glaas, E., Linnér, B.-O., & Neset, T.-S. (2016). Redefining maladaptation. *Environmental Science & Policy, 55*, 135–140.

Karanja Ng'ang'a, S., Bulte, E. H., Giller, K. E., Ndiwa, N. N., Kifugo, S. C., McIntire, J. M., Herrero, M., & Rufino, M. C. (2016). Livestock wealth and social capital as insurance against climate risk: A case study of Samburu County in Kenya. *Agricultural Systems, 146*, 44–54.

Kassie, M., Shiferaw, B., & Muricho, G. (2011). Agricultural technology, crop income, and poverty alleviation in Uganda. *World Development, 39*(10), 1784–1795.

Kassie, M., Teklewold, H., Jaleta, M., Marenya, P., & Erenstein, O. (2015). Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. *Land Use Policy, 42*, 400–411.

Khan, I., Lei, H., Shah, I. A., Ali, I., Khan, I., Muhammad, I., Huo, X., & Javed, T. (2020). Farm households' risk perception, attitude and adaptation strategies in dealing with climate change: Promise and perils from rural Pakistan. *Land Use Policy, 91*, 104395.

Kibue, G. W., Liu, X., Zheng, J., Pan, G., Li, L., & Han, X. (2016). Farmers' perceptions of climate variability and factors influencing adaptation: Evidence from Anhui and Jiangsu. *China. Environmental Management, 57*(5), 976–986.

Le Dang, H., Li, E., Nuberg, I., & Bruwer, J. (2014). Understanding farmers' adaptation intention to climate change: A structural equation modelling study in the Mekong Delta. *Vietnam. Environmental Science & Policy, 41*, 11–22.

Li, L., Jin, J., He, R., Kuang, F., Zhang, C., & Qiu, X. (2022). Effects of social capital on farmers' choices of climate change adaptation behavior in Dazu District, China. *Climate and Development*, 1–12.

Ma, W., & Wang, X. (2020). Internet use, sustainable agricultural practices and rural incomes: Evidence from China. *Australian Journal of Agricultural and Resource Economics, 64*(4), 1087–1112.

MacGillivray, B. H. (2018). Beyond social capital: The norms, belief systems, and agency embedded in social networks shape resilience to climatic and geophysical hazards. *Environmental Science & Policy, 89*, 116–125.

Manda, J., Alene, A. D., Gardebroek, C., Kassie, M., & Tembo, G. (2016). Adoption and impacts of sustainable agricultural practices on maize yields and incomes: Evidence from rural Zambia. *Journal of Agricultural Economics, 67*(1), 130–153.

Miao, S., Heijman, W., Zhu, X., & Lu, Q. (2015). Social capital influences farmer participation in collective irrigation management in Shaanxi Province. *China. China Agricultural Economic Review, 7*(3), 448–466.

Miranda, A. (2004). FIML estimation of an endogenous switching model for count data. *The Stata Journal, 4*(1), 40–49.

Mwongera, C., Shikuku, K. M., Twyman, J., Läderach, P., Ampaire, E., Van Asten, P., Twomlow, S., & Winowiecki, L. A. (2017). Climate smart agriculture rapid appraisal (CSA-RA): A tool for prioritizing context-specific climate smart agriculture technologies. *Agricultural Systems, 151*, 192–203.

Njuki, J. M., Mapila, M. T., Zingore, S., & Delve, R. (2008). The dynamics of social capital in influencing use of soil management options in the Chinyanja Triangle of southern Africa. *Ecology and society*. https://doi.org/10.5751/ES-02539-130209

Ojo, T., & Baiyegunhi, L. (2021). Climate change perception and its impact on net farm income of smallholder rice farmers in South-West. *Nigeria. Journal of Cleaner Production, 310*, 127373.

Omerkhil, N., Chand, T., Valente, D., Alatalo, J. M., & Pandey, R. (2020). Climate change vulnerability and adaptation strategies for smallholder farmers in Yangi Qala District, Takhar. *Afghanistan. Ecological Indicators, 110*, 105863.

Owusu, V. (2016). The economics of small-scale private pump irrigation and agricultural productivity in Ghana. *The Journal of Developing Areas, 50*, 289–304.

Paudel, G. P., Kc, D. B., Justice, S. E., & McDonald, A. J. (2019). Scale-appropriate mechanization impacts on productivity among smallholders: Evidence from rice systems in the mid-hills of Nepal. *Land Use Policy, 85*, 104–113.

Paul, C. J., Weinthal, E. S., Bellemare, M. F., & Jeuland, M. A. (2016). Social capital, trust, and adaptation to climate change: Evidence from rural Ethiopia. *Global Environmental Change, 36*, 124–138.

Priyanath, H., & Lakshika, L. (2020). Social capital, transaction cost and livelihood success: A case of Samurdhi community based organization in Sri Lanka. *International Journal of Management Studies and Social Science Research, 2*(2), 69–83.

Saptutyningsih, E., Diswandi, D., & Jaung, W. (2020). Does social capital matter in climate change adaptation? A lesson from agricultural sector in Yogyakarta. *Indonesia. Land Use Policy, 95*, 104189.

Shikuku, K. M. (2019). Information exchange links, knowledge exposure, and adoption of agricultural technologies in northern Uganda. *World Development, 115*, 94–106.

Takakura, J. Y., Fujimori, S., Hanasaki, N., Hasegawa, T., Hirabayashi, Y., Honda, Y., Iizumi, T., Kumano, N., Park, C., & Shen, Z. (2019). Dependence of economic impacts of climate change on anthropogenically directed pathways. *Nature Climate Change, 9*(10), 737–741.

Tambo, J. A., & Mockshell, J. (2018). Differential impacts of conservation agriculture technology options on household income in Sub-Saharan Africa. *Ecological Economics, 151*, 95–105.

Taruvinga, A., Visser, M., & Zhou, L. (2016). Determinants of rural farmers' adoption of climate change adaptation strategies: Evidence from the Amathole District Municipality, Eastern Cape Province, South Africa. *International Journal of Environmental Science and Development, 7*(9), 687.

Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural Ethiopia. *Journal of Agricultural Economics, 64*(3), 597–623.

Teshome, A., de Graaff, J., & Kessler, A. (2016). Investments in land management in the north-western highlands of Ethiopia: The role of social capital. *Land Use Policy, 57*, 215–228.

Tripathi, A., & Mishra, A. K. (2017). Knowledge and passive adaptation to climate change: An example from Indian farmers. *Climate Risk Management, 16*, 195–207.

Wang, W., Zhao, X., Li, H., & Zhang, Q. (2021). Will social capital affect farmers' choices of climate change adaptation strategies? Evidences from rural households in the Qinghai-Tibetan Plateau, China. *Journal of Rural Studies, 83*, 127–137.

Wolf, J. (2011). Climate change adaptation as a social process. In *Climate change adaptation in developed nations* (pp. 21–32). Springer.

Wooldridge, M. (2003). *Reasoning about rational agents*. MIT Press.

Wossen, T., Berger, T., & Di Falco, S. (2015). Social capital, risk preference and adoption of improved farm land management practices in Ethiopia. *Agricultural Economics, 46*(1), 81–97.

Yaméogo, T. B., Fonta, W. M., & Wünscher, T. (2018). Can social capital influence smallholder farmers' climate-change adaptation decisions? Evidence from three semi-arid communities in Burkina Faso. *West Africa. Social Sciences, 7*(3), 33.

Zainoddin, A., Amran, A., & Shaharudin, M. (2018). The impact of social capital on innovation development Among farmers in Malaysia. AIP Conference Proceedings,

Zakaria, A., Azumah, S. B., Appiah-Twumasi, M., & Dagunga, G. (2020). Adoption of climate-smart agricultural practices among farm households in Ghana: The role of farmer participation in training programmes. *Technology in Society, 63*, 101338.

Zeweld, W., Van Huylenbroeck, G., Tesfay, G., & Speelman, S. (2017). Smallholder farmers' behavioural intentions towards sustainable agricultural practices. *Journal of Environmental Management, 187*, 71–81.

Zhou, J., Liu, Q., & Liang, Q. (2018). Cooperative membership, social capital, and chemical input use: Evidence from China. *Land Use Policy, 70*, 394–401.

Zhuang, Y., Zhang, L., Li, S., Liu, H., Zhai, L., Zhou, F., Ye, Y., Ruan, S., & Wen, W. (2019). Effects and potential of water-saving irrigation for rice production in China. *Agricultural Water Management, 217*, 374–382.