Impact of participation in collective action on farmers' decisions and waiting time to adopt soil and water conservation measures

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Received 22 February 2023
Revised 5 May 2023
25 June 2023
23 October 2023
12 January 2024
29 February 2024
Accepted 18 March 2024

Abstract

Purpose – This study aims to analyze the influence of farmers' degree of participation in collective action on their adoption decisions and waiting time regarding soil and water conservation (SWC) measures.

Design/methodology/approach – The Probit model and Generalized Propensity Score Match method are used to assess the effect of the degree of participation in collective action on farmers' adoption decisions and waiting time for implementing SWC measures.

Findings – The findings reveal that farmers' engagement in collective action positively influences the decision-making process regarding terrace construction, water-saving irrigation and afforestation measures. However, it does not significantly impact the decision-making process for plastic film and ridge-furrow tillage practices. Notably, collective action has the strongest influence on farmers' adoption decisions regarding water-saving irrigation technology, with a relatively smaller influence on the adoption of afforestation and terrace measures. Moreover, the results suggest that participating in collective action effectively reduces the waiting time for terrace construction and expedites the adoption of afforestation and water-saving irrigation technology. Specifically, collective action has a significantly negative effect on the waiting time for terrace construction, followed by water-saving irrigation technology and afforestation measures.

Practical implications – The results of this study underscore the significance of fostering mutual assistance and cooperation mechanisms among farmers, as they can pave the way for raising funds and labor,

International Journal of Climate Change Strategies and Management
Vol. 16 No. 2, 2024
pp. 201-227
Emerald Publishing Limited
1756-8692
DOI 10.1108/IJCCSM-02-2023-0027

cultivating elite farmers, attracting skilled labor to rural areas, enhancing the adoption rate and expediting the implementation of terraces, water-saving irrigation technology and afforestation measures.

Originality/value – Drawing on an evaluation of farmers' degree of participation in collective action, this paper investigates the effect of participation on their SWC adoption decisions and waiting times, thereby offering theoretical and practical insights into soil erosion control in the Loess Plateau.

Keywords Collective action, Soil and water conservation measures, Adoption decision, Waiting time

Paper type Research paper

1. Introduction

The Loess Plateau in China is known for being one of the most severely eroded regions in the world. It is also a key area for soil and water conservation (SWC) and ecological restoration efforts. Soil erosion in this region has led to about 1.7 billion tons of sediment flowing into the Yellow River each year, resulting in an average annual water-level rise of 5∼10 cm. Various factors, including surface, gully, wind erosion and landslides, have caused continued erosion, further depleting the cultivated land. The annual decrease in soil thickness, which is 0.8∼1.0 cm, is over 100 times faster than the speed at which soil is formed. This erosion has resulted in the loss of essential nutrients like nitrogen, phosphorus and potassium, leading to over 60% of the cultivated land suffering from "three losses" – water, soil and fertilizer losses (Zhao *et al.*, 2017). This situation poses a serious threat to both the country's ecological security and food security. Numerous studies have shown that SWC measures can effectively prevent erosion, enhance land productivity, reduce poverty and facilitate agricultural transformation (Kassie *et al.*, 2013; Yin *et al.*, 2022; Prosdocimi *et al.*, 2016; Bogunovic *et al.*, 2018). However, these measures, which offer economic and ecological benefits, have not been widely adopted by farmers (Shangguan *et al.*, 2008; Willy *et al.*, 2014; Jia and Lu, 2020). Consequently, the Loess Plateau still faces urgent ecological issues, including extensive soil and water loss, as well as severe erosion.

Based on the behavioral results, SWC measures yield both agricultural and ecological products. Agricultural products have market value, whereas ecological products are public goods that lack market valuation. Within the household contract management system, cooperative supply by villagers serves as a valuable complement to government-provided public goods, which may have limited supply functions and potential market failures. Cramb (2006) discovered that collective action and training effectively facilitate farmers' implementation of SWC measures in the "Caring for the Land" project in the southern Philippines. Wollni *et al.* (2010) demonstrated through a survey of 241 small-scale farmer households in Honduras that the involvement of collective organizations positively impacts the implementation of SWC measures. Jara-Rojas *et al.* (2013) and Willy and Holm-Müller (2013) conducted separate studies on SWC practices in the Great Lake basins of central Chile and Lake Naivasha in Kenya, respectively. Their findings highlight the significance of joint decision-making and collective action in SWC.

The waiting time for farmers to adopt SWC measures is from the first time when farmers hear about a SWC measure to the time when the measure is adopted. According to the Rational Smallholder School perspective (Mango *et al.*, 2017; Schuler *et al.*, 2016; Zhang *et al.*, 2021), farmers are rational economic agents who possess entrepreneurial thinking (Llewellyn and Brown, 2020; Guo and Jiang, 2022). They strive to maximize output while minimizing input (Beyene and Kassie, 2015). Therefore, upon hearing about a new technology, farmers typically do not make immediate adoption decisions due to the uncertainty of future benefits. Instead, they gather information about its adaptability, cost, operation difficulty, risks, uncertainties, expected benefits and other factors through various channels (Canales *et al.*, 2020). This preliminary evaluation helps them make informed decisions. Farmer groups have been found to be effective in reducing the time farmers take to adopt improved legumes, bananas, maize, etc. based on research in the Great Lakes region of Africa (Ainembabazi *et al.*, 2017). In addition, empirical evidence from Zambia by Manda *et al.* (2020) suggests that cooperative membership can accelerate the adoption of improved maize by 1.6–4.33 years.

Although scholars have studied the impact of collective action on the adoption of SWC measures, two aspects deserve further exploration. First, farmers' degree of participation in public affairs is a key factor influencing the decision and implementation effect of adopting SWC measures. However, most scholars only use a binary variable to express collective action. Second, the impact of collective action on the waiting time to adopt these measures has not been studied. SWC measures are usually implemented through collective cooperation mechanisms, and the more cooperative farmers are, the shorter the waiting time for adopting conservation measures and the faster technology or measures can be adopted. This study uses binary Probit method to analyze the impact of collective action on the decision-making of SWC measures. The Generalized Propensity Score Match (GPSM) method is used to test the impact of collective action on farmers' waiting time to adopt SWC measures. The study focuses on SWC measures that are highly adopted in sample areas, such as terraces [1], water-saving irrigation [2], plastic film [3], afforestation [4] and ridge-furrow tillage [5]. The analysis can provide a theoretical and practical reference for soil erosion control in the Loess Plateau by addressing endogenous and sample selectivity bias.

2. Theoretical analysis

2.1 Impact of collective action on the decision to adopt soil and water conservation measures

SWC measures face several challenges, including high initial investment, long investment recovery period and significant spillover effects. Collective action, however, can encourage farmers to adopt these measures by reducing costs through internal supervision, mutual trust and the establishment of networks. In fact, collective action can facilitate cost-sharing, thereby reducing economic pressure and ultimately facilitating the adoption of SWC measures. As with the diffusion of any technology, the number of initial adopters is comparatively small, but over time, the number gradually increases. As the number of farmers adopting SWC measures increases, collective action can play a critical role in reducing adoption costs, particularly for expenses related to input elements and manpower. The implementation of collective action, mainly through collective procurement, mutual assistance and cooperative implementation, can help farmers obtain economies of scale, alleviate economic pressure and ultimately facilitate the adoption of SWC measures. Studies by Xue *et al.* (2022), Jia and Lu (2020), Kumar *et al.* (2021), and others provide supporting evidence for this viewpoint.

Collective action can effectively prevent free-riding behaviors and ensure the adoption of agricultural technologies and measures because of its supervision function (Zang *et al.*, 2021). According to Ostrom's theory of public resource management (1990), successful cases have in common effective internal supervision and restraint mechanisms. In village settings, collective action is based on geographic and kinship relationships, which foster mutual understanding and establish a complete reputation and internal supervision mechanism through long-term cooperation (Jia and Lu, 2020). To build and maintain a good reputation, most farmers will contribute more to the collective and avoid free-riding or breaking commitments, as these behaviors may result in punishment or exclusion from the collective (Jung *et al.*, 2020). For instance, farmers taking speculative measures must bear higher punishment costs and risk exclusion or marginalization by the collective. Therefore, under collective action's internal supervision mechanism, farmers tend to be more enthusiastic about adopting SWC measures (Li *et al.*, 2021).

Furthermore, collective action can foster mutual understanding, trust and mutual benefits among farmers, thereby promoting the SWC measures (Xue *et al.*, 2022). SWC measures possess characteristics of both private and public goods, as they improve crop yields and ecological conditions. However, implementing these measures on an individual basis can be costly for farmers and lead to conflicts with neighbors, resulting in reluctance to adopt them (Jia and Lu, 2020; Li *et al.*, 2021). Ostrom (1990) emphasized the significance of credible commitment in the management of public resources in her book *Governing the Commons: The Evolution of Institutions for Collective Action*. She stressed that participating in collective actions facilitates the establishment of trust and commitment among farmers. Active engagement in village collective actions enables farmers to communicate, cooperate and gain insights into their neighbors' disposition, skills and personalities, thereby strengthening trust within the community. Moreover, such involvement encourages farmers to honor their commitments (Gao and Arbuckle, 2022). Consequently, based on mutual trust, farmers become more inclined to jointly implement SWC measures.

2.2 Impact of collective action on the waiting time to adopt soil and water conservation measures

Collective action in soil erosion control can accelerate farmers' adoption of SWC measures by leveraging shared resources, fostering social networks, promoting technical knowledge dissemination and clarifying collective members' rights and obligations.

Collective action serves as a key means for farmers to expand social networks, access technical information and expedite the adoption of SWC measures. Villagers' participation in collective activities facilitates knowledge transfer and networking (Ainembabazi *et al.*, 2017; Manda *et al.*, 2020; Kolade and Harpham, 2014). Although modern technology and online resources diversify information sources, most Chinese farmers still rely on social networks for agricultural knowledge because of challenges posed by misinformation, limited content and inefficient traditional promotion systems (Zhang *et al.*, 2009; Zhang *et al.*, 2016; Qiao *et al.*, 2017). Farmer interactions within collective action platforms encompass various topics like production difficulties, costs, outputs, risks, prices and benefits (Ma and Abdulai, 2016; Mojo *et al.*, 2017), enhancing information flow, farmers' discernment and SWC adoption speed.

Furthermore, collective action enables farmers to leverage their collective resources and overcome technical barriers, thereby shortening the time required to adopt SWC measures. SWC measures often demand significant engineering efforts, involve high construction difficulty and require specialized technical expertise. Adoption of these measures is typically guided by technical teams and may require the use of specialized tools and input factors, which may require purchases or leases from specialized equipment suppliers (Jara-Rojas *et al.*, 2013). However, collective adoption allows farmers to pool resources and make use of existing tools and input factors available to other members. Moreover, collective action enables farmers to simultaneously search for technical teams and equipment suppliers, thereby accelerating the process of measure adoption. Because the agricultural technology and equipment markets have uneven capabilities and qualifications, collective cooperation reduces the risk of errors during measure adoption (Gao and Lu, 2021).

In addition, collective actions can address key concerns among members by establishing clear rights and obligations, reducing misgivings and expediting the adoption process through collective consultations. To achieve successful public resource management, it is crucial to have a clearly defined "boundary," in accordance with Ostrom's theory (1990). By providing a detailed explanation of the rights and obligations of members, the issue of free-riding can be effectively avoided. To encourage participation from all members, democratic discussions and meetings can be organized to clarify the obligations, basic rights and daily maintenance of facilities that farmers must fulfill in adopting SWC measures. This approach can dispel farmers' misgivings and shorten waiting time, leading to more successful collective actions. (Zhang *et al.*, 2023). The theoretical framework of this paper is illustrated in Figure 1.

3. Study area and data collection

3.1 Study area

The Loess Plateau, situated in northern central China, stands out as one of the most severely affected regions in terms of soil erosion and ecological fragility worldwide. Spanning over 1,000 km east to west and 750 km north to south, this vast region traverses seven provinces and autonomous regions in China: Qinghai, Gansu, Ningxia, Inner Mongolia, Shanxi, Shaanxi and Henan. Except for a limited number of rocky mountainous regions, the majority of the Loess Plateau is enveloped by substantial deposits of loess. Characterized by fine particles and a loose structure, the loess exhibits a thickness that ranges from 50 to 80 m, reaching up to 150–180 m in some areas. Furthermore, precipitation distribution in the Loess Plateau is markedly uneven, with summer rainfall accounting for 60%–80% of the total annual precipitation, characterized by intense downpours that contribute to heavy erosion. Since the 1950s, local authorities have embarked on commendable endeavors aimed at enhancing the region's ecological environment through the implementation of engineering, biological and cultivation measures focused on SWC.

3.2 Sampling procedure

To investigate the effects of collective action on farmers' adoption decisions and waiting time for SWC measures in the Loess Plateau region, we conducted a field survey using a multistage sampling technique from October to November 2016.

First, based on the principle of typical sampling, we selected Shaanxi, Gansu and Ningxia as the main study areas. These three provinces have significant Loess Plateau landforms and were among the earliest regions to implement soil erosion control measures.

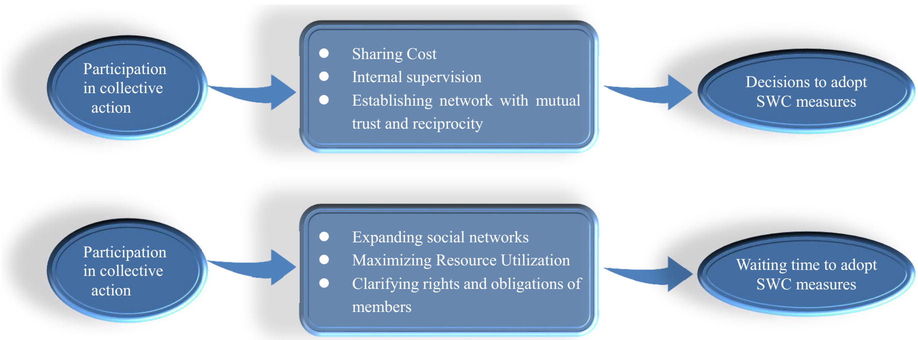

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Figure 1. Theoretical framework

Second, we chose the relatively populated cities of Yulin, Qingyang and Guyuan. Yulin, located in northern Shaanxi, has been a model for ecological governance in the Loess Plateau since the 1950s, implementing measures such as terraced fields, check dams and afforestation. Qingyang in Gansu was once renowned for severe soil erosion in the Loess Plateau. In the 1980s, the total sediment entering the Yellow River in Qingyang reached 168 million tons per year, accounting for 10% of the total sediment discharge in the basin. However, ongoing SWC efforts and ecological governance have reduced sediment discharge by 40% in Qingyang by 2019 [6]. Guyuan in Ningxia is characterized by gullies and belongs to the arid hilly gully and remnant tableland area of the Loess Plateau. It used to be a typical area of ecological vulnerability in the central and southern parts of Ningxia. Through the implementation of various measures, such as terrace construction, afforestation, ridge-furrow cultivation, water storage and water conservation, significant improvements have been made in addressing soil erosion in Guyuan. This comprehensive approach has effectively protected against adverse impacts including flood damage, sediment accumulation and the negative consequences of heavy rainfall.

Third, all the counties of each city were categorized into either three groups: “Excellent,” “Medium” and “Poor”, or two groups: “Good” and “Poor.” Subsequently, one county was randomly selected from each group. As shown in Figure 2, we selected Yuyang District, Mizhi County and Suide County in Yulin city; Xifeng District and Huan County in Qingyang city; and Yuanzhou District and Pengyang County in Guyuan city.

Fourth, a similar sampling methodology was applied to select township samples, where townships within each county were classified into two groups based on the effectiveness of

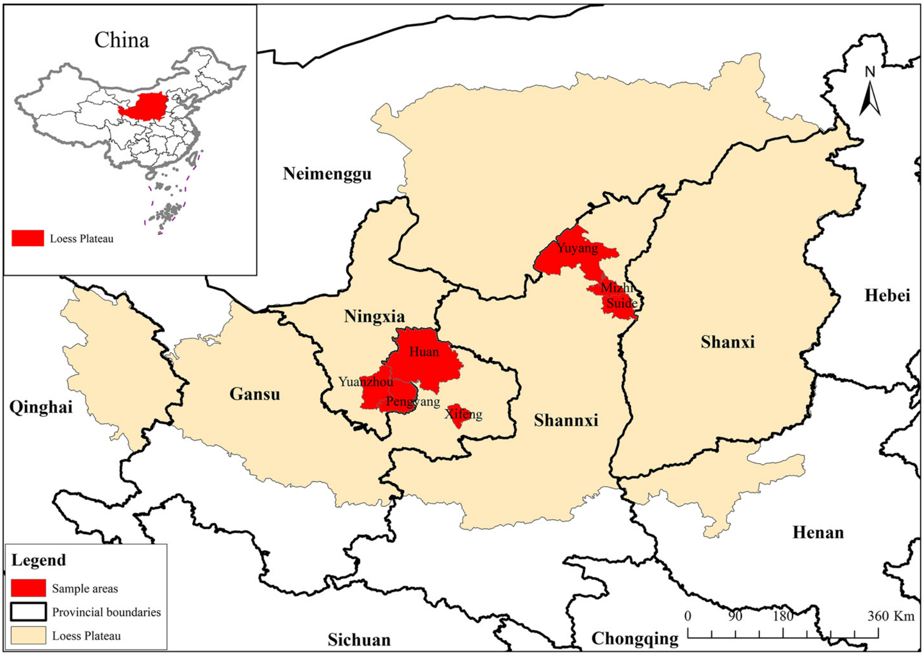

Figure 2.
The location of study area

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SWC measures, namely, “Good” and “Poor.” From each group, one township was randomly chosen.

Fifth, two villages were randomly selected within each township, and 10–15 households with effective communication skills were randomly chosen for interviews. The interview covered topics including individual and family characteristics, participation in collective activities, willingness to adopt SWC measures, decision-making process, waiting time and effects.

We collected data from a total of 936 farming households. To eliminate the interference of outliers, we conducted validity tests on the numerical data in Excel, and reliability tests (Cronbach’s $\alpha = 0.831$) on the scale data using SPSS, including the Likert five-point scale variables related to collective action participation. A total of 87 samples containing abnormal data and missing values were excluded, resulting in a final sample of 849 valid observations. The stringent data processing methods used in this study ensure the reliability and validity of the results obtained.

4. Materials and methods

4.1 Variables and descriptive statistics

4.1.1 Dependent variables. SWC refers to the ecological restoration project, which effectively achieves SWC, soil improvement and increased efficiency of agricultural production technologies through engineering, biological and tillage measures. Among them, engineering measures include not only changing slope, increasing surface roughness and controlling ditches by building terraces, platforms, horizontal ditches, fish scale pits, silt dams and valleys but also water storage engineering measures such as using reservoirs, water cellars, water-saving irrigation technology and plastic film. Biological measures mainly refer to plant measures to control sand, fix sand by covering soil, establishing sand barriers, afforesting and planting grass. Tillage measures include contour tillage, ridge-furrow tillage, less tillage, no-tillage and other measures to change the microtopography of slopes and enhance the soil’s organic matter erosion resistance. During field investigations, the research team found that due to low-cost implementation and management, the desirable effects of water and soil conservation and other related factors, terrace, water-saving irrigation, plastic film, afforestation and ridge-furrow tillage are more commonly adopted by farmers in the Loess Plateau. Therefore, this study takes the decision and waiting time to adopt these five measures as dependent variables to analyze the impact of farmers’ participation in collective action on the adoption of SWC measures. The binary valuation method commonly used in behavioral research is used to represent farmers’ decisions to adopt technology or measures. Specifically, 1 indicates that farmers adopt such measures, whereas 0 indicates that they do not. The waiting time for a technology or measure is defined as the time interval between when a household first hears about a particular measure and when it is actually adopted (Mi *et al.*, 2021; Canales *et al.*, 2020). Drawing inspiration from the studies of scholars such as Ainembabazi *et al.* (2017) and Mi *et al.* (2021), this paper calculates this waiting time by subtracting the year in which a household first hears about the measure from the year in which the household actually adopts the SWC measure.

Table 1 shows that among 849 valid samples, the most adopted practices by farmers were ridge-furrow tillage and plastic film, with 518 and 517 instances, respectively, accounting for 61.01% and 60.9% of all the samples. Furthermore, 428 households built terraces, whereas 310 households participated in afforestation, accounting for 50.41% and 36.51% of all the samples, respectively. In addition, 228 households adopted water-saving irrigation technology, representing 26.86% of all the samples. The waiting time for farmers to adopt SWC measures varied significantly, with terrace construction having the longest waiting time, followed by water-saving irrigation technology, plastic film, afforestation and ridge-furrow tillage.

4.1.2 Independent variables. The independent variable of this paper is the degree of collective action participation among farmers. The primary ways for Chinese farmers to participate in collective action include joining agricultural cooperatives or mutual aid groups involved in crop cultivation, animal husbandry and product sales; participating in rural infrastructure construction projects; engaging in rural public environmental governance initiatives; and participating in rural cultural and recreational programs. The current measures of participation in collective action include those described in the works Dayton-Johnson (2000), who design indicators in terms of participation effects, as well as Kajisa *et al.* (2007), Ito (2012) and Cai and Cai (2014), who design indicators in terms of participation proportions. Furthermore, some scholars have used variables such as the fundraising and labor contribution in village public affairs (Adhikari and Lovett, 2006) and the number of volunteers participating in village public affairs (Cui and Gao, 2023) to represent the degree of collective action participation. However, these variables are all described at the village level and do not capture the participation behavior and participation degree of individual farmers at the micro level. Herein, drawing on the study of Jia and Lu (2020) and Xue *et al.* (2022), who have developed more comprehensive measures of collective action participation, from the perspective of microfarmers, 14 proxy variables are selected to characterize the participation of surveyed farmers in collective action in this paper.

The five variables, which include knowledge of the system, rules, funding, content and meaning, were obtained by interviewing farmers about their understanding of the collective action system, rules, funding utilization, the content and meaning of action. These variables were rated using a Likert scale, where "1" indicated no knowledge, "2" indicated limited knowledge, "3" indicated average knowledge, "4" indicated good understanding and "5" indicated very good understanding. The higher the value of the variable, the greater the level of knowledge the surveyed farmers possessed regarding collective action. According to the statistical results of Figure 3, 217 farmers (25.6%) had good to very good knowledge of the system, 281 farmers (33.1%) had good to very good knowledge of the rules, 168 farmers (19.8%) had good to very good knowledge of funding, 362 farmers (42.6%) had good to very good knowledge of the content and 344 farmers (40.5%) had good to very good knowledge of the meaning of collective action.

The training participation rate variable was obtained by dividing the average number of times farmers participated in training per year by the average number of times per year that training was conducted collectively. The meeting participation rate variable was obtained by dividing the average annual number of collective meetings actually attended by farmers by the average annual number of meetings held collectively. From the statistical results in

Table 1. Descriptive statistics of dependent variables

Types of measures	No. of households adopting WSC measures	Adoption ratio (%)	Waiting time (year) Mean	SD	Min	Max
Terrace	428	50.412	16.523	9.317	0	45
Water-saving irrigation	228	26.855	8.092	4.927	0	20
Plastic film	517	60.895	2.222	1.242	0	5
Afforestation	310	36.514	2.416	1.413	0	10
Ridge-furrow tillage	518	61.013	0.390	1.210	0	9

Source: Authors' own creation

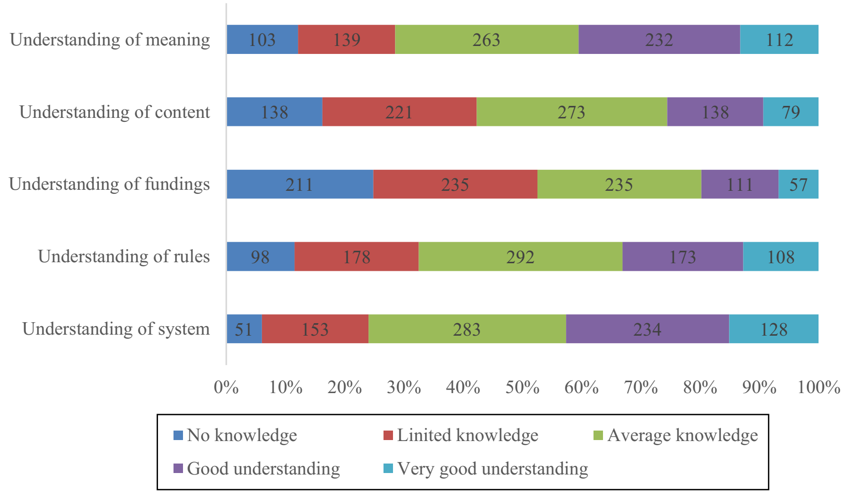

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Figure 3. Distribution of information in collective action

Figure 4, it can be seen that the participation of the interviewed farmers in collective training is relatively high, with an average participation rate of 71.3%. However, farmers were less enthusiastic about participating in collective meetings, with an average participation rate of less than 50%.

The proportion of the capital contribution variable is equal to the actual amount of money contributed by the farmer to the collective organization divided by the amount required to be contributed by the collective organization in 2015. The proportion of the labor contribution variable is equal to the actual working hours of the farmers in the collective organization divided by the hours required by the collective organization in 2015. From the statistical results in Figure 5, it is evident that the average percentage of capital contribution and the percentage of labor contributed by the interviewed farmers do not differ significantly and are both relatively high, being 71.5% and 72.6%, respectively.

The organization variable measures the role of family members in the collective organization, with "1" as a bystander, "2" as a participant, "3" as a manager, "4" as a leader and "5" as an initiator in collective action. The statistics in Figure 6 show that 1% of the

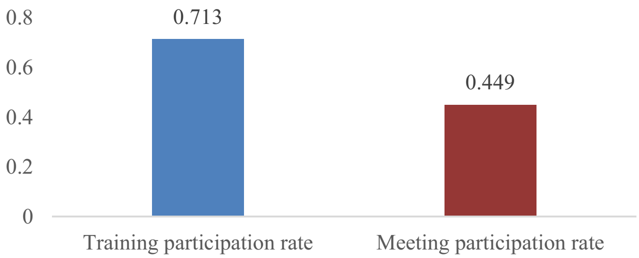

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Figure 4. Mean of training and meeting attendance ratios

interviewed farmers were bystanders, 63% were participants, 21% were managers, 9% were leader, and only 6% were initiators.

The four variables, which include increased income, improved environment, enhanced relations and improved infrastructure, were obtained by interviewing farmers about the effects of collective action on farm income, ecological environment, relations between villagers and infrastructure. These variables were also rated on a Likert scale, with "1" indicating particularly bad, "2" indicating bad, "3" indicating fair, "4" indicating relatively good and "5" indicating especially good. The higher the value of the variable, the more satisfied the surveyed farmers were with the effectiveness of collective action. The statistical results in Figure 7 show that 297, 356, 396 and 422 interviewed farmers rated the

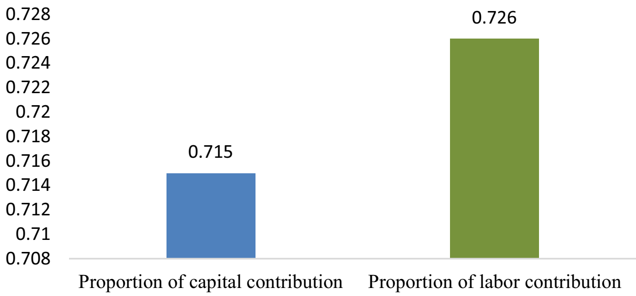

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Figure 5.
Average of capital and labor input ratios

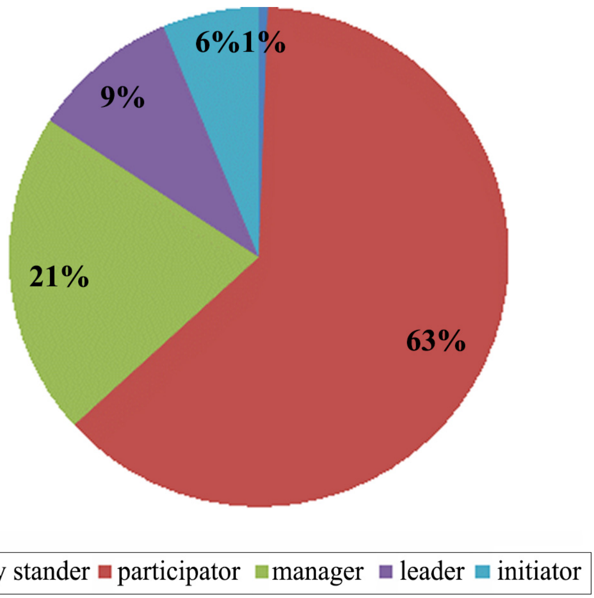

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Figure 6.
Distribution of different roles in public affairs

effectiveness of collective action in increasing income, improving the ecological environment, enhancing villagers' relationships, and improving infrastructure conditions as relatively good or exceptionally good, accounting for 35.0%, 41.9%, 46.6% and 49.7% of the total sample, respectively.

4.1.3 Control variables. Referring to the studies of the adoption decision and adoption speed of environmentally friendly agricultural technologies, which have environmental spillover effects, such as water-saving technology (Mi *et al.*, 2021), SWC measures (Cheng *et al.*, 2020; Li *et al.*, 2021), climate-smart farming technologies (Olawuyi and Mushunje, 2020; Jabbar *et al.*, 2023; Kreft *et al.*, 2023), organic farming technologies (Manda *et al.*, 2020) and no-tillage techniques (Xue *et al.*, 2022), we selected control variables from household characteristics, family characteristics, planting situations, government support, social networks, regional features, etc. to avoid the interference on the regression results. Householder characteristics variables included age, the square of age and years of education. Family background was shown by variables such as whether family affairs were decided by women, whether there were village cadres among family members, the number of family members and house value. Planting situation was reflected by the actual planting area of farmers (calculated as "contracted area + leased area − rented area"). Government support was characterized by the amount of government subsidies received in 2015 and whether they accepted the technical services provided by the government. The level of social network was shown by the number of relatives and friends interacting frequently. Ningxia was used as the control group, whereas "Shaanxi" and "Gansu" were included to reflect the impact of location (Table 2).

In the waiting time model of SWC measures, in addition to the aforementioned control variables, the manpower and material input variables that may affect waiting time were also included [7]. The manpower input variable is determined by multiplying the number of individuals by the duration of their work, whereas the material input variable is calculated by adding the cost of purchasing special means of production during the adoption of the measure. During our field visits, we found that the majority of water-saving irrigation facilities were provided by professional companies, therefore, requiring no labor input from farmers. Farmers participating in the Chinese "Grain for Green" project did not need to purchase tree seedlings as the government provided them for free. In addition, farmers implementing ridge-furrow tillage measures only needed to contribute their labor, without any additional financial investment. Consequently, we excluded the manpower input variable from the water-saving irrigation waiting time model, as well as the financial input variable from the afforestation and ridge-furrow tillage waiting time models.

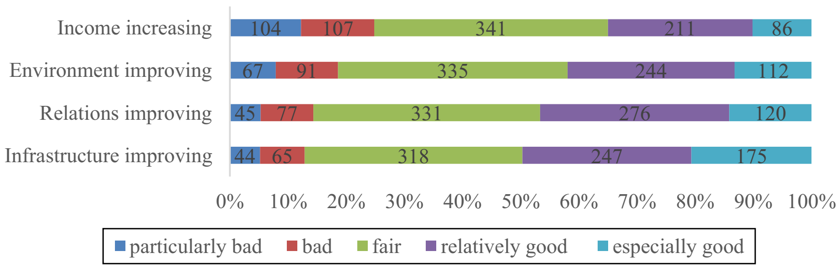

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Figure 7. Distribution of behavior effect

Table 2. Descriptive statistics of control variables

Variables	Mean	SD	Sample size	Variables	Mean	SD	Sample size
Householder's age (years old)	51.597	12.018	849	Number of close friends and relatives (person)	51.656	60.354	849
Square of the householder's age	2806.528	1224.443	849	Shaanxi (yes = 1/no = 0)	0.350	0.477	849
Years of household's education (years)	5.921	3.806	849	Gansu (yes = 1/no = 0)	0.319	0.466	849
Female is the decision-maker (yes = 1/no = 0)	0.425	0.495	849	Manpower input on terrace (person × day)	9.063	10.342	428
Village cadre (yes = 1/no = 0)	0.140	0.347	849	Material input on terrace (in 10,000 yuan)	0.043	586.328	428
Number of the family members (person)	4.572	1.979	849	Material input on water-saving irrigation (in 10,000 yuan)	0.072	203.625	228
House value (in 10,000 yuan)	6.451	6.947	849	Manpower input on plastic film (person × day)	0.511	0.643	517
Planting area (hm^2)	0.761	0.837	849	Material input on plastic film (in 10,000 yuan)	0.006	33.499	517
Government subsidies (in 10,000 yuan)	0.290	0.539	849	Manpower input on afforestation (person × day)	11.716	5.431	310
Technology promotion (yes = 1/no = 0)	0.419	0.494	849	Manpower input on ridge-furrow tillage (person × day)	1.656	0.768	518

Source: Authors' own creation

4.2 Research method and model

4.2.1 The measure method of participation degree of collective action. Drawing on the study of Jia and Lu (2020), this paper chooses principal component analysis to measure the degree of collective action participation of the sample farm households. According to the results of the analysis with the data of 849 sample farm households using the SPSS 21.0 software, the Kaiser-Meyer-Olkin (KMO) value of collective action-related variables is 0.769 and the likelihood ratio (LR) statistic is 11,911.192, with a significance of 0.000, indicating that such variables pass the KMO test and LR test, and the data are suitable for principal component analysis.

Second, to make the principal component analysis results have a more reasonable economic meaning, the maximum variance method is selected in this paper to rotate the original matrix and extract the m principal components with characteristic roots greater than 1.

Finally, the principal component scores of the m dimensions of collective action participation degree are weighted and summed by the variance contribution of each principal component separately to calculate the index of farmers' collective action participation degree, which was calculated by the following formula:

$$T_i = \vartheta_1 \times F_{i1} + \vartheta_2 \times F_{i2} + \cdots + \vartheta_m \times F_{im} \tag{1}$$

In the formula, T_{i} is farmer i's participation degree in collective action, $F_{\mathrm{i1}} \sim F_{\mathrm{im}}$ are the scores of each principal component of farmer i, and $\vartheta_1 \sim \vartheta_{\mathrm{m}}$ are the weights of principal components.

There are four principal components with characteristic roots greater than 1 are extracted from the sample data. The variance contributions of principal components 1, 2, 3 and 4 are 23.768%, 21.312%, 20.665% and 13.738%, respectively, with a cumulative variance contribution of 79.484%. Therefore, the degree of collective action participation of sample farmers can be calculated according to the following formula. The classification results of variables related to collective action are shown in Figure 8:

$$T_i = (23.768 \times F_{i1} + 21.312 \times F_{i2} + 20.665 \times F_{i3} + 13.738 \times F_{i4})/79.484 \tag{2}$$

4.2.2 Binary Probit model for the impact of collective action on the adoption decision of SWC measures. The decision whether to adopt SWC measures or not is a binary variable. Drawing inspiration from the studies of scholars such as Wang *et al.* (2016) and Tang *et al.* (2019), the binary Probit model with strong explanatory power for behavior decision-making is used to test the influence of collective action participation on the farmers' decision to adopt SWC measures. The model is as follows:

$$P(Y_{ij} = 1 | T_i) = \Phi(\alpha_{i_j} + \beta_{i_j} T_i + \gamma'_{i_j} X_i + \varepsilon_{ij}) \tag{3}$$

In the above formula, $\Phi(*)$ is the cumulative distribution function; Y_{ij} is farmer i's adoption decision of No. j SWC measure (1 = yes); T_{i} is farmer i's participation degree in collective action; X_{i} represents control variables; α_{ij}, β_{ij} and γ'_{ij} are parameters to be evaluated; and ε_{ij} represents unobserved errors.

4.2.3 Generalized Propensity Score Match method for the impact of collective action on waiting time to adopt soil and water conservation measures. To avoid the impact of selection bias on the regression results, more and more scholars choose the counterfactual inference model to explore the correlation between variables (Koomson *et al.*, 2023; Zhu and Yu, 2023). According to the research of Bia and Mattei (2008), Egger and Von Ehrlich (2013)

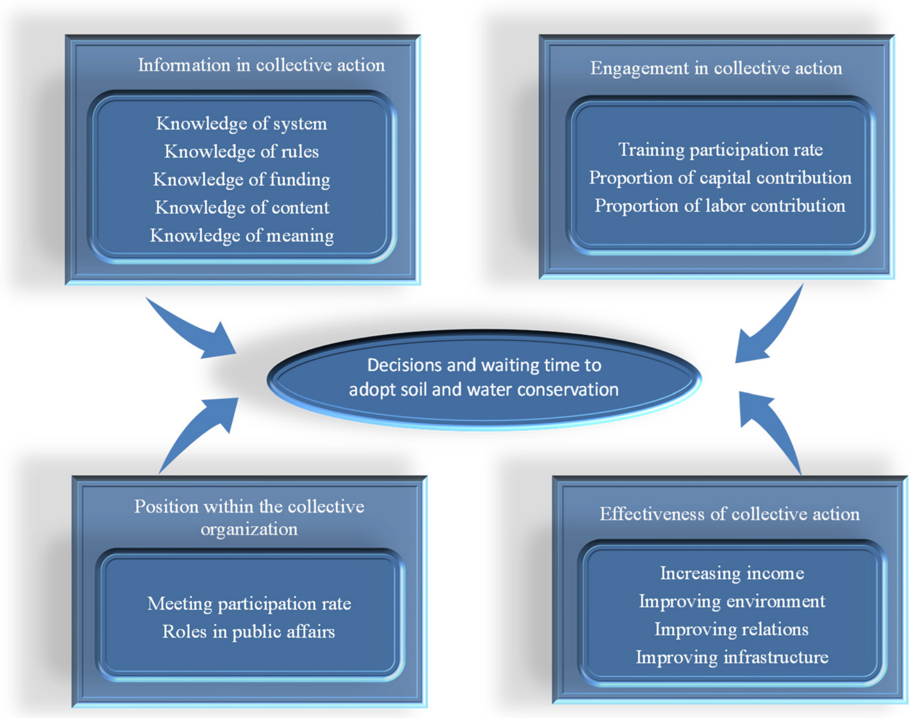


Figure 8.
Variables of collective action and adoption of soil and water conservation

Source: Authors' own creation

and Austin (2019), we choose GPSM to test the impact of collective action participation degree on the waiting time. There are two major reasons for using GPSM in this article. First, compared with the Tobit model commonly used by scholars to analyze continuous truncated variables, GPSM does not have the endogenous problem caused by the missing variables between farmers' participation degree in collective action and their waiting time to adopt SWC measures. It can eliminate the sample selectivity bias on regression results, making the results more robust. Second, GPSM can match continuous treatment variables, which effectively fills the gap of traditional PSM (the traditional PSM can only match binary treatment variables). With reference to the practices by Lei (2022) and Yu *et al.*(2023), the analysis steps in this article are as follows:

- Select matching variables, use the maximum likelihood method to estimate the conditional distribution function of treatment variables (degree of participation in collective action) and calculate the generalized propensity score (GPS) of sample farmers.
- Establish the model of outcome variables (waiting time) through continuous treatment variables (degree of participation in collective action) and GPS. Estimate the parameters by ordinary least squares:

$$E\left(Q_{ij}|T_i, \widehat{GPS_{ij}}\right) = \hat{\upsilon}_{ij} + \hat{\kappa}_{ij}T_i + \hat{\theta}_{ij}\widehat{GPS_{ij}} + \hat{\omega}_{ij}T_i * \widehat{GPS_{ij}} \quad (4)$$

In the formula, Q_{ij} is farmer i's waiting time to adopt No. j SWC measure; T_i is farmer i's degree of participation in collective action; $\hat{GPS}_{ij}$ is farmer i's generalized propensity score on No. j SWC measure; $\hat{\upsilon}_{ij}$, $\hat{\kappa}_{ij}$, $\hat{\theta}_{ij}$ and $\hat{\omega}_{ij}$ are the parameters to be estimated:

- According to the parameters obtained in Step (2), the average expected values of waiting time for different SWC measures are estimated in each interval of treatment variables (degree of participation in collective action), respectively.

$$E\left(\hat{Q}_j(T)\right) = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{\upsilon}_{ij} + \hat{\kappa}_{ij}T_i + \hat{\theta}_{ij}\widehat{GPS}_{ij} + \hat{\omega}_{ij}T_i * \widehat{GPS}_{ij}\right) \tag{5}$$

In the formula, n is the number of sample farmers in each interval of treatment variables. The effect curve is obtained by connecting the coefficients and their confidence intervals.

5. Results and discussion

5.1 Impact of the degree of participation in collective action on farmers' decision to adopt soil and water conservation measures

We used the Stata14 software to examine the influence of participating in collective action on the adoption of SWC measures. The results from the Probit models presented in Table 3 indicate that the LR statistics of all adoption decision models, including terrace, water-saving irrigation, plastic film, afforestation and ridge-furrow tillage, successfully pass the significance test at the 1% level.

The results of the Probit models show that the degree of farmers' participation in collective action has a positive effect on the adoption of terrace, water-saving irrigation and afforestation measures. These findings are consistent with previous research by Manda *et al.* (2020) and Xue *et al.* (2022), which demonstrated a positive correlation between cooperative membership or participation in collective action and the probability of technology adoption in agriculture. The more farmers participate in the supply of public goods and public resource management in villages, the more likely the adoption of these measures becomes.

Constructing terraces and installing water-saving irrigation equipment involves substantial initial investment and a longer payback period, often requiring the assistance of professional companies (Jia and Lu, 2020). Higher levels of household participation in village collective activities are associated with a stronger willingness to seek and evaluate suppliers, negotiate with them collectively, thereby increasing the likelihood of adopting terracing and water-saving irrigation technologies (Llewellyn and Brown, 2020; Olawuyi and Mushunje, 2020; Manda *et al.*, 2020; Mi *et al.*, 2021). Even though afforestation does not require professional companies, the organization of village collective activities helps households unite and purchase tree seedlings and tools collectively, making implementation costs more manageable and increasing the likelihood of adoption. However, the degree of collective action participation did not have a significant impact on the adoption decision of plastic mulch and furrow cultivation practices. This indicates that the adoption decision regarding plastic film and ridge-furrow tillage is primarily influenced by family or natural conditions, whereas the degree of participation in village collective action has no significant impact on farmers' decisions. This outcome may be attributed to the relatively lower difficulty in implementing these measures and the minimal cost difference between individual and collective adoption, with individual adoption offering greater flexibility. Furthermore, comparison of regression coefficients from different models reveals that, in

Table 3.
Regression results of binary probit models

Variables	Terrace	Water-saving irrigation	Plastic film	Afforestation	Ridge-furrow tillage
Degree of participation in collective action	0.808*** (0.252)	2.588*** (0.567)	0.123 (0.164)	0.969*** (0.211)	0.166 (0.164)
Householder's age	0.095** (0.048)	−0.011 (0.094)	0.091*** (0.035)	−0.026 (0.042)	0.089** (0.035)
Square of householder's age	−0.001** (0.001)	−0.001 (0.001)	−0.001*** (3.000E-04)	2.000E-04 (4.000E-04)	−9.000E-04*** (3.000E-04)
Years of householder's education	0.050** (0.023)	0.172*** (0.057)	0.046*** (0.016)	0.055*** (0.019)	0.045*** (0.016)
Female is the decision-maker	0.032 (0.198)	0.422 (0.429)	0.219 (0.144)	−0.457*** (0.170)	0.232 (0.144)
Village cadre	0.677 (0.540)	0.488 (0.488)	−0.855*** (0.211)	0.942*** (0.218)	−0.882*** (0.211)
Number of close friends and relatives	−0.002 (0.001)	−0.003 (0.003)	3.000E-04 (8.000E-04)	−7.000E-04 (9.000E-04)	2.000E-04 (8.000E-04)
Number of family members	0.015 (0.037)	−0.093 (0.087)	−0.001 (0.025)	−0.007 (0.028)	−0.006 (0.025)
Planting area	−0.002 (0.006)	0.001 (0.013)	0.013*** (0.004)	−0.004 (0.005)	0.013*** (0.004)
House value	0.001 (0.011)	0.004 (0.022)	−0.019** (0.007)	0.009 (0.008)	−0.019** (0.007)
Government subsidies	0.972*** (0.256)	1.715*** (0.499)	−0.196 (0.128)	0.540*** (0.166)	−0.186 (0.128)
Technology promotion	1.289*** (0.152)	2.649*** (0.369)	1.168*** (0.136)	−0.112 (0.132)	1.157*** (0.136)
Shaanxi	−2.177*** (0.189)	−1.820** (0.833)	−0.213 (0.132)	1.415*** (0.165)	−0.202 (0.132)
Gansu	−1.140*** (0.171)	4.422*** (0.514)	−0.266** (0.126)	0.057 (0.154)	−0.257** (0.126)
Constant	−1.385 (1.175)	−3.862* (2.061)	−2.214** (0.861)	−0.516 (1.034)	−2.147** (0.861)
Observations	849	849	849	849	849
Pseudo R2	0.614	0.895	0.168	0.374	0.167
LR chi2(14)	722.32***	883.90***	191.24***	416.81***	189.25***

Notes: ***, **, and * indicate significance at the levels of 1, 5 and 10%, respectively data in parentheses are standard deviation
Source: Authors' own creation

comparison with the adoption of terrace and afforestation measures, the degree of participation in collective action has a greater impact on the adoption decision of water-saving irrigation technology. This indicates that the adoption of water-saving irrigation technology is more reliant on collective actions, likely due to the involvement of professional companies in the installation of water-saving irrigation facilities. Farmers may encounter difficulties and challenges in finding professional companies if they engage in independent installation (Jia and Lu, 2017a; Jia and Lu, 2017b).

The age and education level of the householder were found to be significant factors influencing the adoption decisions of terrace, plastic film and ridge-furrow tillage measures. Specifically, the householder's age exhibited an inverted U-shaped relationship with the adoption probabilities of these measures, with middle-aged households having a higher likelihood of adoption. This finding is consistent with previous research on adoption of water-saving irrigation technologies. Furthermore, the education level of the householder was found to have a positive impact on the adoption probability of terrace, water-saving irrigation, plastic film, afforestation and ridge-furrow tillage measures, indicating that higher education levels may lead to a deeper understanding of soil erosion issues and greater enthusiasm for implementing various SWC measures, as observed in previous studies by Cheng *et al.* (2020), Li *et al.* (2021) and Xue *et al.* (2022). The significance test confirmed that female farmers prioritize the land's basic functions of food production and income generation compared with male farmers when making afforestation decisions. They have a lower inclination to engage in public affairs, resulting in a decreased interest in reforestation (Jia and Lu, 2019; Lu, 2021). The presence of village cadres in the household significantly influences the adoption decisions regarding plastic film, afforestation and ridge-furrow tillage measures. The presence of village cadres has a significant positive impact on the adoption decision for afforestation measures, whereas it has a significant negative impact on the adoption decisions for plastic film and ridge-furrow tillage measures. Village cadres, as key advocates, organizers and supervisors in project implementation, exhibit greater enthusiasm for participating in afforestation compared with other villagers (Jia and Lu, 2019; Li *et al.*, 2021). However, their engagement in traditional agricultural practices involving plastic film and ridge-furrow tillage is comparatively lower. In addition, the significance test indicates that planting area and house value play a role in the adoption decision models for plastic film and ridge-furrow tillage. The coefficient for planting area is positive, implying that a larger planting area corresponds to a higher proportion of agricultural income and a greater willingness among farmers to adopt plastic film and ridge-furrow tillage practices to enhance production and income. Conversely, the coefficient for house value is negative, as it reflects farmers' income and possessions. The adoption of SWC measures in China's affluent rural households depends on various factors. Liu and Li (2017) found that affluent rural families are usually part-time agricultural or non-agricultural households with diverse sources of income and less dependence on agricultural production, which could explain their low enthusiasm for SWC measures like using plastic film and ridge-furrow tillage. However, results from the adoption decision model of terrace, water-saving irrigation and afforestation show that higher government subsidies can significantly promote farmers' adoption of these SWC measures (Jia and Lu, 2018; Huang, 2019; Cheng, 2020). Similarly, technology promotion by government and scientific research institutions can motivate the adoption of SWC measures, apart from afforestation. The reason why technology dissemination activities have no impact on the implementation of afforestation measures may be that afforestation is relatively easy, and farmers can implement it without special technical guidance (Cheng *et al.*, 2020). Location variables also play a role in the adoption of SWC measures. In Shaanxi, a higher proportion of farmers adopts afforestation, whereas a lower proportion adopts terrace and water-saving irrigation, compared to Ningxia. On the contrary, in Gansu, a higher proportion of farmers adopt water-saving irrigation, whereas a lower proportion adopts terrace, plastic film and ridge-furrow tillage.

5.2 Impact of participation in collective action on farmers' waiting time to adopt soil and water conservation measures

The regression results of the adoption decision model for SWC measures indicate that the degree of collective action participation does not significantly affect the adoption of plastic film and ridge-furrow tillage measures. Therefore, this study focuses on the impact of collective action participation on farmers' waiting time to adopt terrace, water-saving irrigation and afforestation measures. Table 4 presents the initial step of the GPSM and the estimated results of the conditional distribution function for the treatment variable (degree of collective action participation). Wald's statistics demonstrate a good fit for the waiting time models of terrace, water-saving irrigation and afforestation. The main factors influencing farmers' participation in collective action include the years of education of the household head, the gender of the decision-maker, the presence of village cadres in the family, the number of close relatives and friends, house value, government subsidies, technology promotion and location. To calculate farmers' GPS and test the balance of these variables, the treatment variable was divided into three groups based on tertiles (−0.22 and 0.22). Samples were matched, and the differences in matching variables between groups were individually tested (Cui *et al.*, 2018). The overall balance of matching variables in each model passed the 1% significance test, substantially mitigating sample selectivity bias.

Table 5 presents the estimated results of the second step of GPSM. The *F*-values of the terrace, water-saving irrigation and afforestation waiting time regression models in Table 5 all pass the 1% significance test, indicating a good fit of the models. Furthermore, the coefficients of collective action in all models have passed significance test at the 1% level and are negative. These results indicate that collective action can effectively reduce the waiting time for farmers to construct terraces, adopt water-saving irrigation technologies and engage in afforestation activities. The adoption of terracing, water-saving irrigation technology and afforestation measures requires a significant amount of labor and involves high levels of technical complexity and specialization (Cheng *et al.*, 2020; Li *et al.*, 2021). The higher the level of participation of farmers in rural public affairs, the more channels they have to access knowledge and information related to terracing, water-saving irrigation and afforestation activities. Communication and cooperation among households in collective activities can effectively broaden the information channels available to households, significantly reducing uncertainties in the adoption of various technologies (Mi *et al.*, 2021). Furthermore, the rules and order established by households during long-term cooperation processes help clarify the rights and obligations of collective members in the adoption of terracing, water-saving irrigation technology and afforestation measures, reducing conflicts and disputes (Cheng, 2020), enabling households to adopt these measures more promptly. These findings are consistent with the conclusions drawn by Ainembabazi *et al.* (2017), Manda *et al.* (2020) and Mi *et al.* (2021), who also found that cooperative members tend to adopt technology more swiftly.

Through a comparison of the coefficients of different measures in waiting time models, it can be concluded that collective action has the most significant effect on shortening the waiting time for terrace construction, followed by water-saving irrigation technology and afforestation measures. This is likely because of the complex and time-consuming nature of terrace construction, which requires extensive cooperation and collective planning among villages. Such collective action can improve farmers' cohesion and sense of community, thus

Table 4. Regression results of factors influencing the participation degree of collective action

Variables	Terrace Coefficient	Terrace Standard error	Water-saving irrigation Coefficient	Water-saving irrigation Standard error	Afforestation Coefficient	Afforestation Standard error
Householder’s age	−0.005	0.013	0.008	0.019	0.003	0.012
Square of householder’s age	0.199E-04	1.000E-04	−0.569E-04	2.000E-04	−0.232E-04	1.000E-04
Years of householder’s education	0.002	0.005	−0.002	0.007	0.009*	0.005
Female is the decision maker	−0.461***	0.033	−0.380***	0.047	−0.435***	0.038
Village cadre	0.221***	0.043	0.085*	0.048	0.188***	0.052
Number of close friends and relatives	2.000E-04	2.000E-04	6.000E-04**	3.000E-04	−0.101E-04	2.000E-04
Number of family members	−0.011	0.008	0.003	0.009	−0.006	0.007
Planting area	0.001	0.001	−3.000E-04	0.001	8.000E-04	0.001
House value	0.006***	0.002	0.005**	0.002	0.001	0.002
Government subsidies	0.199***	0.027	0.169***	0.029	0.187***	0.029
Manpower input	−0.001	0.002			0.002	0.003
Material input	−0.093	0.259	−1.180	0.844		
Technology promotion	0.111***	0.035	0.035	0.071	−0.019	0.036
Shaanxi	−0.111**	0.051	−0.354***	0.073	−0.319***	0.043
Gansu	−0.200***	0.034	−0.552***	0.049	−0.386***	0.042
Constant	0.361	0.300	0.488	0.441	0.317	0.301
Observations	428		216		310	
Wald chi2(14)	727.12***		604.48***		702.98***	

Notes: ***, ** and * are significance at the levels of 1, 5 and 10% respectively. Farmers’ waiting time to adopt SWC measures is the specific years from the first time when they hear about the measures to the time when they actually adopt them. Because the waiting time of farmers who do not adopt the measures cannot be obtained, the number of samples put in the regression analysis of waiting time is the number of farmers who adopt various measures
Source: Authors’ own creation

Variables	Terrace Coefficient	Terrace Standard error	Water-saving irrigation Coefficient	Water-saving irrigation Standard error	Afforestation Coefficient	Afforestation Standard error
Degree of participation in collective action	−22.280***	1.018	−10.597***	1.285	−1.297***	0.375
GPS	−4.053***	0.653	−2.184***	0.754	−0.202	0.220
Degree of participation in collective action*GPS	5.111***	0.990	2.769***	0.977	0.935***	0.309
Constant	25.317***	0.764	13.800***	1.063	2.747***	0.295
Observations	428		216		310	
F-value	383.33***		63.73***		4.62***	
Observations	0.731		0.474		0.043	
Adj R-squared	0.729		0.467		0.034	

Note: *** Indicates significance at the levels of 1%
Source: Authors' own creation

Table 5.
Regression results of the GPSM models

reducing the waiting time for construction. In addition, the disparity in average waiting times for each measure may also contribute to the difference in average waiting time of each measure (average waiting time for terrace > average waiting time for water-saving irrigation > average waiting time for afforestation, see Table 1 for details).

The third step of GPSM is to estimate the "dose-response" function and the causal effect curve according to Formula (5) (Lei, 2022; Yu *et al.*, 2023). We made the "dose-response" functions and the causal effect curves between the waiting time of SWC measures and participation degrees of collective action. The variations in waiting time for SWC measures were attributed to changes in the participation degree of collective action, as the GPSM model mitigated differences of covariates effectively (Bia and Mattei, 2008; Egger and Von Ehrlich, 2013; Austin, 2019). According to the regression results in Table 6, it can be observed that the impact of collective action on waiting times for the three SWC measures passed the significance tests at different participation degrees, except for the 1.3

Participation degree of collective action	Waiting time for terrace Estimation value	Waiting time for terrace Standard error	Waiting time for water-saving irrigation Estimation value	Waiting time for water-saving irrigation Standard error	Waiting time for afforestation Estimation value	Waiting time for afforestation Standard error
−1.4	56.508***	3.733	28.636***	7.482	4.563***	1.621
−1.1	49.793***	3.141	25.457***	6.495	4.173***	1.382
−0.8	42.772***	2.480	22.253***	5.501	3.764***	1.133
−0.5	34.944***	1.652	18.811***	4.344	3.285***	0.826
−0.2	26.999***	1.062	15.022***	2.967	2.830***	0.493
0.1	20.062***	0.673	11.192***	1.494	2.527***	0.245
0.4	14.732***	0.579	8.542***	0.796	2.380***	0.223
0.7	9.476***	0.924	6.238***	0.734	2.111***	0.353
1	3.284**	1.615	3.419***	1.074	1.658***	0.569
1.3	−3.480	2.403	0.271	1.841	1.145	0.835

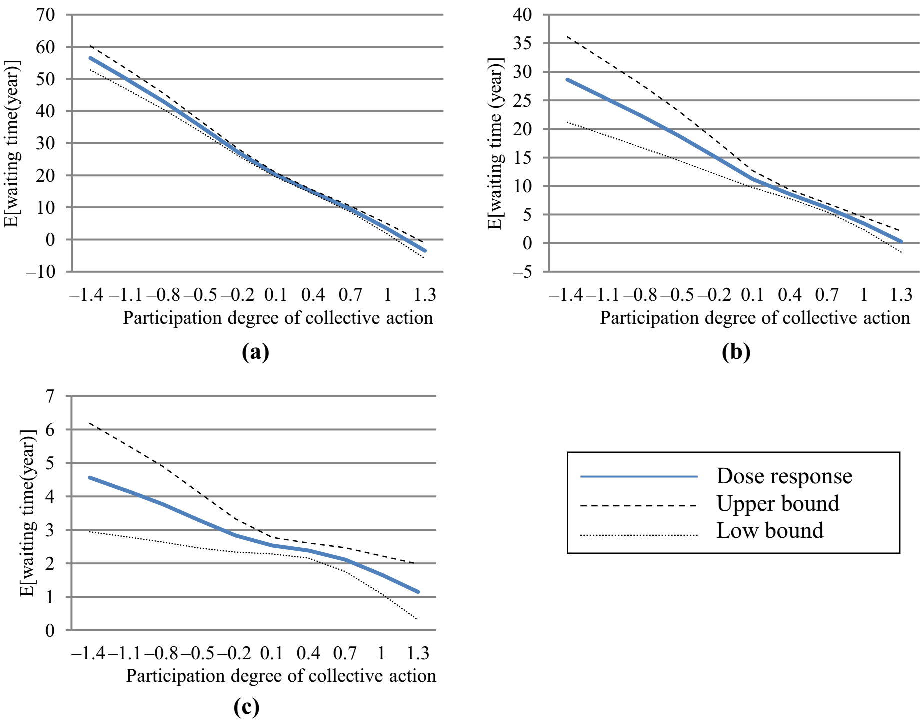
Note: ** and * indicate significance at the levels of 1 and 5%, respectively
Source: Authors' own creation

Table 6.
Estimation results of the dose-response functions

participation degrees. The trend of effect curves in Figure 9 suggested that the higher the participation degree of collective action, the shorter the waiting time for farmers, which is consistent with the regression results of the second step. Furthermore, under each participation degree of collective action, farmers have the longest waiting time for the terrace, followed by water-saving irrigation techniques and afforestation. The results are consistent with the results of descriptive statistical analysis.

6. Conclusions and policy implications

Based on data collected from 849 rural households in three Chinese provinces, this study examined the impact of farmers' degree of participation in collective action on their adoption decisions and waiting time for SWC measures. The main research findings are as follows: The degree of farmers' participation in collective action has a significant and positive impact on the adoption of terracing, water-saving irrigation technologies and afforestation measures in agriculture. However, it does not have a discernible impact on the adoption of measures such as plastic film and ridge-furrow tillage. In other words, increased participation of farmers in the supply of public goods and the management of public resources in rural areas significantly increases the probability of adopting terrace, water-saving irrigation technology and afforestation measures. Specifically, collective action



Notes: (a) Terrace; (b) water-saving irrigation; (c) afforestation
Source: Authors' own creation

Figure 9.
Graphs of the dose-response functions

has a greater influence on farmers' adoption decisions regarding water-saving irrigation technology, whereas its impact on the adoption of afforestation and terracing measures is relatively smaller. Participating in collective action proves effective in reducing the waiting time for farmers to implement terrace construction, adopt water-saving irrigation technology and carry out afforestation measures. The impact of collective action on the waiting time is most pronounced for terrace construction, followed by water-saving irrigation technology and afforestation measures.

This study provides significant implications for policymakers based on its findings. As highlighted by Ostrom (1990), mutual trust, detailed rules, internal supervision mechanisms and the initiator of collective action are essential guarantees for successful collective action implementation. Therefore, it is imperative for the government to concentrate on establishing a mutual assistance and cooperation mechanism among farmers. Ensuring that farmers have adequate access to raising funds and managing labor is a crucial step toward this goal. Furthermore, the government should actively cultivate elite farmers by selectively appointing village cadres or attracting skilled individuals to rural areas. Promoting collective cooperation is essential in enhancing the adoption of SWC measures and reducing the waiting time concurrently.

This study has several limitations. First, restricted by the limited number of sampled households and the types of SWC measures adopted in the surveyed regions, this study only investigates the adoption behavior and waiting time of certain SWC measures, such as terraces and water-saving irrigation. Other equally effective measures, such as platforms, check dams, silt dams and gully head protection, have not been studied. Second, updated data is necessary to explore possible changes in collective action behavior after the COVID-19 pandemic. Third, due to limitations in the length of the paper, this study does not explore the heterogeneity in the impact of farmers' collective action of different scales on the adoption behavior and waiting time of SWC measures. This will be a future direction for our research efforts.

Notes

1. Terraces are fields with strip-shaped step-like or wavy-shaped cross-sections built along contour lines on hilly slopes.
2. Water-saving irrigation technologies refer to a series of technical measures in the field of agriculture and horticulture that aim to reduce water usage, improve water utilization efficiency and enhance irrigation systems and management methods. Common water-saving irrigation technologies in China include drip irrigation, sprinkler irrigation, micro-sprinkler irrigation and seepage irrigation.
3. Plastic film is a technology that involves covering the surface of the soil with a layer of plastic film to maintain soil temperature and humidity, reduce soil erosion, and alter crop growth conditions.
4. Afforestation can stabilize the soil through plant roots, protecting it from erosion caused by water and wind.
5. Ridge-furrow tillage is an agricultural method that involves digging narrow trenches in the fields, piling the soil from the trenches to form ridges and planting crops on the ridges. This method helps to maintain soil moisture while improving drainage and enhancing soil fertility.
6. www.gov.cn/xinwen/2020-07/03/content_5523900.htm
7. Farmers not adopting SWC measures do not have the manpower and material input, so the adoption decision model does not include the manpower and material input variables of various measures.

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