Promoting sustainable agrifood production under climate change: practices and outcomes

Abstract

Climate change is challenging sustainable agrifood production and food security, and encouraging farmers' climate change adaptation can help promote sustainable agrifood production and ensure food security. This study investigates farmers' climate change adaptation and its impact on agrifood production. We employ the propensity score matching (PSM) model to address the selection bias issue of climate change adaptation and estimate the survey data collected from 415 rice-producing households in rural China. We also estimate the inverse probability weighted regression adjustment (IPWRA) model for robustness check. The empirical results show that farmers' decisions on climate change adaptation are influenced by household heads' age, education level, life satisfaction, temperature perception, and transportation conditions. The treatment effect estimations of the PSM model reveal that climate change adaptation significantly increases land productivity by 41.24-44.29% and labor productivity by 55.06-63.72% in rice production. The IPWRA model estimation largely confirms the robustness of the PSM model estimation. We also find that climate change adaptation significantly increases the net returns of rice production. These findings have significant global implications. By understanding the factors influencing farmers' decisions to adapt to climate change, policymakers worldwide can design targeted interventions to encourage similar practices in other regions. Promoting farmers' climate change adaptation to increase farm productivity is crucial for ensuring global food security in the face of ongoing climate challenges.

Keywords: Sustainable agrifood production; climate change adaptation; returns to land and labor; food security

JEL codes: J24, O13, Q24, Q55

1 Introduction

The global agrifood system comprises food production, processing, packing, storage, transportation, retail, consumption, loss, and waste (Heydari, 2024; IPCC, 2019). To be sustainable, the agrifood system is expected to meet the food demand of the present and future generations while maintaining profitability and reducing environmental pollution. Sustainable agrifood production is the origin and prerequisite of the whole agrifood system. It is critical to overcome the conflict between population growth and natural resources, reduce adverse environmental influences, and ensure global food supply (McGreevy et al., 2022). However, climate change events, such as extreme droughts and heat, frequent floods, and irregular precipitation patterns, have challenged sustainable agrifood production (Bryan et al., 2024; IPCC, 2023; Maggio et al., 2022). It is reported that, in Mauritania, the 2014 drought led to an 11.9% lower per capita consumption and an 8.9% higher likelihood of falling below the poverty line (Ba and Mughal, 2022). Chen and Gong (2021) found that extreme heat reduces China’s agricultural total factor productivity and input utilization in the short run, resulting in a more negative effect on yield. Therefore, it is crucial to address the challenges of climate change for the agrifood sector.

In practice, farmers are switching from outdated practices to climate-resilient technologies to adapt themselves to the changing climate and achieve sustainable agrifood production goals. The climate-resilient technologies adopted by farmers include, for example, minimum tillage and zero tillage, diversifying seeds and crops, integrated pest management, and applying organic fertilizer and farmyard manure (Amadu et al., 2020; Asmare et al., 2022; Autio et al., 2021; Bairagi et al., 2020; Bhatta et al., 2022; Zheng et al., 2024). As emphasized by the Food and Agriculture Organization (FAO), these “climate-smart” strategies are expected to achieve or even synergize three objectives: (a) sustainably increasing agricultural productivity and incomes, (b) adapting and building resilience to climate change, and (c) reducing greenhouse gas emissions.

Recent studies have provided evidence of the positive influences of climate change adaptations on crop yield and farm income (Asmare et al., 2022; Gorst et al., 2018; Khanal et al., 2018; Wang et al., 2022). They mainly focus on yield and income effects, measuring yield and income based only on returns to land. Nevertheless, research gaps remain. Because investments in climate-smart practices are associated with additional capital and labor inputs and household labor division, climate change adaptations may also influence labor demand and returns to labor (Hörner and Wollni, 2022). Sesmero et al. (2018) found that adverse weather history prompts households to work more on maize cultivation on their farms in Malawi. To date, it is unclear whether adaptation to climate change can contribute to returns to labor in agrifood production.

This study extends the findings of existing literature by examining farmers' climate change adaptation and its impact on agrifood production. Climate change adaptation is captured by whether or not a farming household has adopted improved varieties and/or soil and water conservation practices. We utilize survey data from 415 rural households that participated in rice production in China. China's rice sector is facing challenges from the increasing temperature. Chen and Chen (2018) reported that global warming would decrease the average rice yield in China by 10-19% by 2050. In addition, the world population is expected to reach 9.1 billion by 2050; meanwhile, food production is expected to increase by 70% (FAO, 2009). To feed the world, it is said that 90% of growth in crop production globally should come from higher crop yield and increased production intensity (FAO, 2009). To improve crop yield, it is essential to understand whether rice farmers' adaptations to climate change can effectively help improve agrifood production.

This study's originality includes three aspects. First, we examine two indicators of agrifood production from the perspective of factor returns: land productivity and labor productivity. Diverging from existing studies that primarily concentrate on crop yield or land productivity alone (Arslan et al., 2015; Khanal et al., 2018; Wang et al., 2022), our study integrates labor productivity, a facet often overlooked. Agricultural labor productivity captures rural households' labor allocation and returns to farming (Restuccia, 2016; Zhang et al., 2020). Second, the study utilizes a propensity score matching (PSM) technique to address the self-selection bias when estimating the impact of climate change adaptation on agrifood production. A plausible endogeneity concern exists, given that farmers autonomously make decisions regarding adaptation strategies. By matching farmers who have adopted climate change adaptation measures with those who have not, PSM effectively addresses this endogeneity issue while estimating treatment effects (Abid et al., 2016; Khan et al., 2021; Ma et al., 2022). Third, in addition to the two indicators of factor returns, we further examine the effects of climate change adaptation on the net returns of rice production. This facet holds significance as net returns, delineated as the disparity between farm revenue and variable costs, encapsulate additional expenditures that are not accounted for within land and labor productivity metrics.

The remainder of this paper proceeds as follows—section 2 reviews relevant literature. Section 3 introduces empirical strategy. Section 4 presents the data source and the descriptive statistics. Section 5 presents and discusses empirical results, while the final Section 6 highlights the key conclusions and policy implications.

2 Literature review

A growing number of studies investigate the effects of climate change adaptation on agrifood production and rural household wellbeing. Within this domain, the literature delineates three primary thematic avenues of inquiry: the influence on poverty alleviation and risk mitigation, the ramifications on food security and household welfare, and the effects on agricultural yields and income generation.

The first strand delves into the nexus between climate change adaptation measures and their efficacy in alleviating poverty and mitigating risks (Ho and Shimada, 2021; Issahaku et al., 2020; Sarr et al., 2021; Shahzad and Abdulai, 2020; Tesfaye et al., 2021). For example, Issahaku *et al.* (2020) analyzed Ghana's climate change adaptations of smallholder farming households. Adopting adaptation strategies (i.e., irrigation, soil conservation, and enhanced cropping calendar management) as a package reduces multi-dimensional poverty and downside risk exposure. Tesfaye et al. (2021) found that climate-smart innovations, including minimum tillage, cereal-legume intercropping, and their combination, reduce the incidence and depth of poverty in Ethiopia, indicating their risk mitigation role. Sarr et al. (2021) reported that the rice intensification system significantly reduces the downside risk of crop failure in Tanzania.

The second strand delves into the intricate relationship between climate change adaptations and the overarching concerns of food security and household welfare (Bairagi et al., 2020; Bazzana et al., 2022; Issahaku and Abdulai, 2020; Martey et al., 2021, 2020; Shahzad and Abdulai, 2021). For example, using household survey data from Ghana, Issahaku and Abdulai (2020) observed that adopting climate-smart practices (soil and water conservation and crop choices) positively and significantly impacts food and nutrition security. Martey et al. (2020) found that adopting row planting and drought-tolerant maize varieties, two representative climate-smart agriculture practices increases both yield and intensity of maize commercialization but negatively affects consumption in Ghana. In the study on climate-smart agricultural (CSA) practices in Pakistan, Shahzad and Abdulai (2021) showed that adopting CSA practices (i.e., change in cropping calendar, diversified seed varieties, changing input mix, and soil and water conservation measures) significantly reduces household food insecurity and increases household dietary diversity.

The third strand centers on elucidating the ramifications of climate change adaptation strategies on agricultural yields and income dynamics (Bazzana et al., 2022; Khan et al., 2021; Lachaud et al., 2021; Maggio et al., 2022; Vatsa et al., 2024; Wang et al., 2022; Wouterse et al., 2022). For example, Wang et al. (2022) found that farmers' adaptation to climate change significantly increases rice yields in China. Maggio et al. (2022) showed that adopting organic fertilizer and maize-legume intercropping positively affects the total value of crop production in Uganda. Focusing on shrimp aquaculture in Vietnam, Do and Ho (2022) reported that the adoption of upgrading pond dikes and settling pond is associated with increased productivity in shrimp farming.

Generally, efficiency in agrifood production has been primarily expressed in terms of yield (kg per unit of land) or farm income (value per unit of land) in the existing literature. However, productivity increases for a sustainable agrifood system, and more dimensions, such as labor productivity, should be considered (FAO, 2018). Studies investigating the relationship between climate change adaptations and labor productivity remain scarce. In this study, we aim to provide empirical evidence on farmers' climate change adaptation and its impact on agrifood production, captured by two indicators related to factor returns: land productivity and labor productivity. This study could supplement existing literature by enriching our understanding from the perspective of labor productivity in agrifood production systems (Fentie and Beyene, 2019).

3 Empirical strategy

3.1 Self-selection bias issue and model selection

We assume a linear relationship between climate change adaptation and returns to land and labor. The empirical model for examining the relationship between climate change adaptation and agrifood production can be specified as a general agricultural production function:

$$Y_i = \alpha_0 + \alpha_a A_i + \alpha_x X_i + \varepsilon_i \tag{1}$$

where Y_i refers to the dependent variables, including land productivity and labor productivity, for household i; A_i captures the climate change adaption status; X_i represents other explanatory variables that are expected to affect the outputs; α_0 is a constant; α_a and α_x are the corresponding parameters; ε_i is a error term. In particular, α_a is used to capture the effect of climate change adaptation on the dependent variable. If $\alpha_a > 0$ and is statistically significant, suggesting that climate change adaptation increases land productivity or labor productivity and vice versa.

It is up to farmers whether they should adapt to climate change, as it is a self-determined process. Farmers' demographic and farm-level characteristics tend to influence their climate change adaptation decisions (Asmare et al., 2022; Fentie and Beyene, 2019; Issahaku and Abdulai, 2020; Martey et al., 2020). These facts lead to a potential selection bias issue of variable A_i in Equation (1). Failing to account for the selection bias would generate biased and inconsistent estimates and mislead the policy implications.

When experimental data have been collected through randomization, causal inference can be made through the counterfactual situation. However, our survey data were collected in a non-random context, which cannot directly provide information on the counterfactual scenario. Therefore, it is necessary to infer the direct effect of climate change adaptation from the variation in outcomes across rural households using non-experimental approaches.

Previous studies have employed both instrument variable (IV) based methods and non-parametric approaches to address the selection bias issue of a dichotomous treatment variable. The IV-based methods include, for example, two-stage least square (2SLS) regression and endogenous switching regression (ESR) model (Issahaku and Abdulai, 2020; Midingoyi et al., 2019; Vatsa et al., 2024; Wang et al., 2022). The non-parametric approaches include, for example, the PSM technique (Fentie and Beyene, 2019; Gorst et al., 2018; Khanal et al., 2019; Ma et al., 2022) and inverse probability weighted regression adjustment (IPWRA) estimator (Addison et al., 2020; Danso-Abbeam and Baiyegunhi, 2018; Zheng and Ma, 2021). It bears an emphasis here that a valid IV should meet strict criteria of exogeneity, and sometimes it is difficult to identify an ideal IV in the available observational data. Bowden et al. (2016) and

Ma et al. (2022) pointed out that failure to use the valid IV in the IV-based estimations would yield inconsistent estimates. We employed the PSM in the present study because we could not find a reasonable IV in our dataset. We also utilize the IPWRA estimator for robustness checks.

3.2 Propensity score matching approach

The PSM approach involves a two-step process. In the first step, a probit model estimates the probability that farming households choose to adapt to climate change. The following specification can express it:

$$A_i^* = \beta_i Z_i + \mu_i, A_i = \begin{cases} 1, if\ A_i^* > 0 \\ 0, otherwise \end{cases} \tag{2}$$

where A_i^* is the latent variable, representing the probability that household i adapts to climate change. Although A_i^* is unobservable, it could be represented and observed by A_i: $A_i = 1$ for climate change adapters and $A_i = 0$ for non-adapters. Z_i refers to a vector of control variables, including the household- and farm-level characteristics, and β_i is the corresponding parameters to be estimated. μ_i refers to an error term.

The second step calculates the treatment effects of climate change adaptation. In essence, the PSM model facilitates the calculations of the average treatment effects (ATE), average treatment effects on the untreated (ATU), and average treatment effect for the treated population (ATT). The ATT is the most popular (Fentie and Beyene, 2019; Khanal et al., 2019; Ma et al., 2022). In the present study, we are also interested in estimating ATT, expressed as follows:

$$ATT = E(Y_1 - Y_0|A = 1) = E(Y_1|A = 1) - E(Y_0|A = 1) \tag{3}$$

where Y_1 denotes the dependent variable (land productivity or labor productivity) when households adapted to climate change, and Y_0 is the value of the same variable when a household did not adapt to climate change. $E(Y_1|A = 1)$ refers to the expected dependent variable for the treated group in the observed scenario, whereas $E(Y_0|A = 1)$ is the expected dependent variable for the treated group in the counterfactual scenario.

Several matching techniques have been employed in previous studies to calculate the ATT, such as kernel-based matching (KBM), nearest neighbor matching (NNM), and caliper-based matching (CBM) (Kim et al., 2020; Ma et al., 2022; Zhang et al., 2020). Each technique has advantages and disadvantages, so it is helpful to use comprehensive methods when estimating treatment effects and evaluating their robustness. For example, using both KBM and NNM techniques, Ma et al. (2022) assessed the impact of information acquisition on nutrition intake and found robust causal positive effects. Similarly, we estimate the impacts of climate change adaptation on land productivity and labor productivity utilizing both the KBM and NNM (1-5) techniques.

4 Data source and descriptive statistics

4.1 Data source

The data for this study was collected by a household survey implemented between January and February 2022. The survey area covers five provinces in China, namely Jiangsu, Henan, Hubei, Hunan, and Sichuan. Among them, Jiangsu and Sichuan are located in the eastern and western regions, respectively, while Henan, Hubei, and Hunan are in the central regions. The different agroecological conditions across provinces would capture the heterogeneous responses to climate change adaptations. The samples were selected in a four-stage sampling framework. The first stage includes the purposive selection of five provinces, and the second involves randomly selecting around 8-10 counties in each province. Subsequently, the third and fourth stages involve randomly choosing 1-2 villages in each county and approximately 10 households in each village. Because not all respondents participated in farm production and the returns to land and labor are different across crops, we only focused on respondents who cultivated rice in the 2021 farming season for consistent estimations. The final sample of 415 observations is used in the empirical analyses.

Our structured questionnaire covers various modules, enabling enumerators to collect data through face-to-face interviews. To capture returns to land and labor, we collected detailed information on inputs (e.g., land size, family labor, and hired labor) and outputs (e.g., yields and sale price) of rice production. In particular, we asked farmers to report the number of family laborers participating in rice production and their working days. In addition, the number of hired laborers for rice production was also collected. We aggregate the number of labor-day for family labor and hired labor as total labor use, accounting for the shadow uses of unpaid labor.

We employ value- (farm revenue) rather than quantity-based (yield) measurement of rice output to account for the potential effects of the heterogenous market price. Specifically, land productivity is measured as rice output per unit of land (Yuan/mu), and labor productivity is measured as rice output per unit of labor-day (Yuan/labor-day). We define climate change adaptation as a dummy variable capturing adopting improved varieties and/or soil and water conservation practices. Improved varieties refer to insect/disease-resistant or stress-tolerant varieties (Hörner and Wollni, 2022), while soil and water conservation practices refer to minimum tillage (Aryal et al., 2018). Though climate change adaptation strategies include many techniques across different agroecological environments, crops, and countries (Do and Ho, 2022; Ho et al., 2022; Issahaku et al., 2020; Wang et al., 2022), focusing on improved varieties and soil and water conservation practices enables us to compare and estimate our results from a general view.

4.2 Descriptive statistics

The variable definition and summary statistics are presented in Table 1. It shows that the average land productivity is 670.63 Yuan/mu, and the average labor productivity is 59.53 Yuan/labor-day. More than half of households (54%) have adopted adaptation strategies to climate change. Approximately 65% of household heads are male, and their average age is 54. Household heads possess an average education level of 6.95 years. In terms of self-rated life satisfaction, they report being satisfied with their lives on average, scoring 4.06 out of 5. There are around 4-5 residents per household, and they own an average of 8.18 mu of land for rice production. Approximately 58% of households have electronic bicycles, and 20% have access to agricultural information extension agents. The average distance to the nearest train station is 40.39 kilometers, and the average distance to the nearest credit source is 2.61 kilometers. In our sample, households from Jiangsu, Henan, Hubei, Hunan, and Sichuan account for 13%, 15%, 19%, 27%, and 26%, respectively.

[Insert Table 1 here]

The differences in the means of household demographic and farm-level characteristics variables between climate change adapters and non-adapters are presented in Table 2. The last column in Table 2 reports the mean differences and the corresponding statistical significances. The upper part of Table 2 shows that regarding land productivity, climate change adapters obtain 743.07 Yuan/mu, which is 158.62 Yuan/mu higher than non-adapters. The difference is significant at the 5% level. The labor productivity for adapters is also 29.70 Yuan/mu higher than that for non-adapters, though the mean difference is insignificant. Regarding control variables, the results show that the household heads in the climate change adapters tend to have lower life satisfaction than their non-adapter counterparts. The family size for climate change adapters is smaller than for non-adapters. Compared to non-adapters, climate change adapters are less likely to live in villages with an agricultural information extension agent. The distance to the train station and credit source for the adapters is longer than for the non-adapters. However, the simple mean difference test produces unsolid results since confounding factors are not addressed, leading to misleading conclusions. Therefore, this study employs the PSM method to address the sample selection bias and estimate the unbiased effects of climate change adaptation on agricultural outcomes.

[Insert Table 2 here]

5 Results and discussions

5.1 Propensity score estimations and matching quality tests

5.1.1 Propensity score estimations

Table 3 presents the Probit model's results, estimated by Equation (2). Estimating Equation (2) mainly aims to generate propensity scores for matching while providing valuable insights into the determinants of adaptation to climate change. We interpret the results below to enrich our understanding of the pros and cons of farmers' adaptation decisions. We present the coefficients and corresponding marginal effects in the second and third columns of Table 3.

[Insert Table 3 here]

The marginal effect of the age variable is 0.005 and statistically significant at the 5% level, indicating that one-year increase in household head's age is associated with a 0.5% higher probability of adapting to climate change. The finding echoes the results of Asmare *et al.* (2022) on Ethiopia. They found that the likelihood of implementing climate change adaptation is positively associated with the age of respondents. An additional year of education would increase the propensity of farmers' adaptation decisions by 1.3%. Higher education levels enable farmers to learn more about farm innovations and motivate them to make adaptation decisions. This aligns with the results of Kangogo et al. (2021), who reported that education is positively associated with adopting certified seed and soil testing. Interestingly, household heads' life satisfaction is negatively related to their decisions to adapt to climate change. Another unit increase in life satisfaction is related to a 9.0% lower probability of adaptation decisions. Those satisfied with their life would be less likely to change their cropping patterns because climate change adaptation requires additional capital investment and labor inputs.

The marginal effect of temperature perception is positive and statistically significant, indicating that rice farmers who perceive severe temperature change are more likely to adapt to climate change. The positive and statistically significant marginal effect of the transportation variable suggests that an additional kilometer increase in the distance to the nearest transportation station would increase the probability of adapting to climate change by 0.2%. Aryal et al. (2022) report similar findings: a longer distance to the nearest main market positively relates to farmers' decisions to change farming practices in Ethiopia. Policymakers worldwide can consider these findings when planning transportation networks and market accessibility projects. Governments can enhance the likelihood of adopting climate-resilient practices by ensuring farmers have better access to transportation and markets. Farmers' adaption decisions tend to be influenced by locational heterogeneities. Specifically, compared with farmers in Sichuan (reference province), those in Henan have an 18% higher probability of adapting to climate change.

5.1.2 Matching quality tests

Before formal testing the matching quality of the propensities derived using the Probit model, it is instructive to check the number of observations for which the propensity scores of climate change adapters and non-adapters in the sample. To this end, we examine the propensity score distribution of climate change adapters and non-adapters. Figure 1 presents the distribution of propensity scores before and after matching. The visual inspection of the distribution of the estimated propensity scores for households with and without treatment (i.e., climate change adapters and non-adapters) indicates that the common support condition is satisfied.

[Insert Figure 1 here]

Using the KBM and NNM methods, we test matching quality and present the results in Table 4. There is a significant reduction in Pseudo R^2 and mean bias after matching (see columns 3 and 4) compared to the statistics before matching (see column 2). Table 4 also presents the likelihood ratio test of the joint significance of all the regressors in the Probit model before and after matching. The LR χ^2 values show that the significance of regressors on treatment status is jointly insignificant. All the evidence suggests our matching process successfully eliminates the potential bias between climate change adapters and non-adapters arising from the control variables and achieves the covariate balance.

[Insert Table 4 here]

5.2 Treatment effects of adaptation on returns to land and labor

Table 5 presents the treatment effects (ATTs) of climate change adaptation on agrifood production, captured by land productivity and labor productivity. Before explaining the estimated results, we utilize the Rosenbaum (2002) bound test to verify the sensitivity of the estimated ATTs. The results of Rosenbaum's sensitivity analysis for the presence of hidden bias are presented in Table A1 in the Appendix. It shows that the treatment effects are robust to hidden bias for Gamma values as high as two. Thus, the ATTs estimated by the two PSM techniques are pure effects of adaptation to climate change.

[Insert Table 5 here]

In Table 5, both KBM and NNM (1-5) estimations show that farmers' climate change adaptation positively impacts land productivity and labor productivity. All estimated ATTs except the estimate for labor productivity by the KBM estimator are statistically significant. Specifically, farmers who adapt to climate change would obtain 41.24-44.29% higher land productivity than their counterparts. This finding is largely in line with the finding of Abid et al. (2016), showing that climate change adaptation significantly and positively affects wheat productivity in Pakistan. Khan et al. (2021) also reported similar results in their study on the relationship between farm-level autonomous climate change adaptation and crop productivity in Pakistan. Regarding the treatment effects on labor productivity, it shows that the labor productivity of climate change adapters is 55.06-63.72% higher than that of counterfactuals. The findings indicate that apart from returns to land, returns to labor can also be improved through climate change adaptation. Thus, by fostering a more inclusive approach to technology adoption and climate change adaptation, countries can better equip their agricultural sectors to withstand the challenges posed by climate change, thereby contributing to global food security and sustainable agricultural development.

We further utilize the IPWRA estimator to check the robustness of ATTs estimated by the PSM technique. The IPWRA also owns features that eliminate selection bias related to a binary treatment variable and evaluate ATTs (Hörner and Wollni, 2021; Ma et al., 2022). The robustness check results estimated by the IPWRA estimator are presented in Table A2 in the Appendix. It provides similar results to Table 5. Climate change adaptation significantly increases land productivity by 38.97%, and its impact on labor productivity is positive, though statistically insignificant. Overall, our findings suggest that climate change adaptation is an effective way for rice farmers to increase returns to land and labor; the additional investments and labor inputs arising from climate change adaptation pay off.

5.3 Treatment effects of adaptation on net returns

Although climate change adaptation is related to significant increases in land productivity and labor productivity, the costs arising from additional capital and labor inputs are still neglected. Because of this, we construct the variable net returns, which are defined as the difference between farm revenue and variable costs. Net returns are preferred as they account for production costs (Hörner and Wollni, 2022; Zheng et al., 2021). The effects of climate change adaptation on net returns are presented in Table A3 in the Appendix. The results show that ATTs estimated by KBM and NNM techniques are positive and statistically significant, indicating that climate change adaptation also significantly increases net returns. Thus, we can confirm that the extra inputs associated with climate change adaptations are profitable investments. Policymakers in various regions can leverage this evidence to advocate for and implement policies supporting climate adaptation strategies, ensuring these investments yield economic benefits and environmental sustainability.

6 Conclusion and policy implications

Farmers' climate change adaptation is critical for sustainable agrifood production and food security, which previous studies have emphasized. Nevertheless, the adaptations are usually associated with additional inputs for capital and labor and household labor division. Whether these investments pay off for smallholder farmers is rarely investigated and lacks empirical evidence. Accordingly, this study estimates the impact of climate change adaptation on agrifood production, focusing on two indicators of factor returns: land productivity and labor productivity. For the empirical analysis, we utilize the PSM technique to control the selection bias associated with farmers' adaptation decisions and estimate the rural household survey data collected from five provinces in China. Specifically, both KBM and NNM approaches are employed to ensure the validity of estimation results. We estimate the IPWRA estimator for robustness check.

We first employ the Probit model to generate propensity scores and explore determinants of adaptation to climate change. The results show that farmers' adaptation decisions are positively associated with the household heads' age and education, temperature perception, and transportation conditions. In contrast, the life satisfaction of the household head negatively affects adaptation to climate change. Further, the results of KBM and NNM suggest that adapting to climate change is associated with significant increases in land and labor productivity. On average, the treatment effects of climate change adaptation are to increase land productivity by 41-44% and labor productivity by 55-64%, respectively. The ATTs estimated by the IPWRA technique also support the positive effects of climate change adaptation on returns to land and labor. We also find that climate change adaptation significantly increases net returns.

The findings have practical implications for rice farmers, stakeholders, and policymakers. Overall, the findings of this study underline the importance of climate change adaptation in boosting agrifood production by increasing returns to land and labor. This confirms the positive role of climate change adaptation in welfare improvement from an innovative perspective of factor returns. Thus, encouraging farmers' climate change adaptation would promote sustainable agrifood production and food security.

Though climate change adaptation is essential to increase land productivity and labor productivity, not all farmers are willing to take adaptation actions. We find that old and better-educated farmers are more likely to adapt to climate change. Therefore, governments globally should aim to enhance awareness among younger and less-educated farmers about the adverse impacts of climate change on crop production and encourage them to adopt adaptation strategies. Policymakers in various regions can achieve this by developing inclusive technology adoption programs. For example, training initiatives can be organized in collaboration with local farmers' organizations to provide practical, hands-on learning experiences. Furthermore, these strategies should be tailored to different regions' specific cultural and socio-economic contexts to maximize their effectiveness.

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Figures

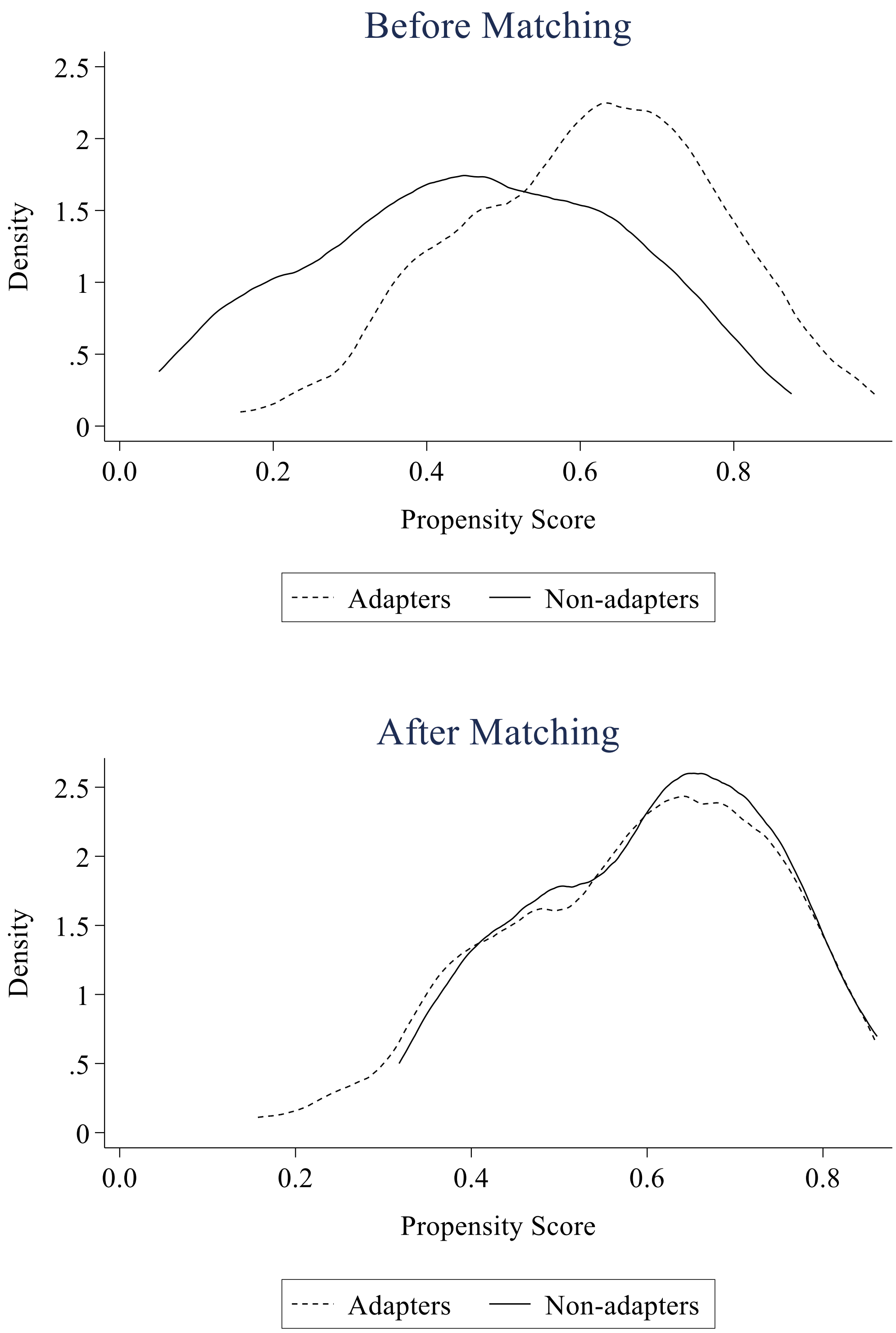

Figure 1 Density distribution of propensity scores for adapters and non-adapters before and after matching

Tables

Table 1 Variable definition and summary statistics

Variables	Measurements	Mean (S.D.)
Dependent variables		
Land productivity	Rice output per unit of land (Yuan/mu) [a]	670.63 (722.36)
Labor productivity	Rice output per unit of labor (Yuan/labor-day)	59.53 (186.04)
Climate change adaptation	1 if household has adopted improved varieties (e.g., Insect/disease-resistant or stress-tolerant varieties) and/or soil and water conservation practices (e.g., minimum tillage), 0 otherwise	0.54 (0.50)
Independent variables		
Age	Age of household head (years)	53.90 (12.55)
Gender	1 if household head is male; 0 otherwise	0.65 (0.48)
Education	Educational years of household head (years)	6.95 (3.95)
Life satisfaction	Self-reported life satisfaction level of household head: 1=very unsatisfied; 2=unsatisfied; 3=fair; 4=satisfied; 5=very satisfied	4.06 (0.88)
Family size	Number of family members (persons)	4.50 (1.54)
Farm size	Total land size for rice cultivation (mu) [a]	8.18 (27.69)
Asset ownership	1 if household owns electronic bicycle(s), 0 otherwise	0.58 (0.49)
Access to extension	1 if agricultural information extension agents exist in the local village, 0 otherwise	0.20 (0.40)
Pest experience	1 if household experienced pest attack during rice production, 0 otherwise	0.12 (0.32)
Temperature perception	Self-reported perception of temperature change in the last five years: 1=Extremely severe; 2=Severe; 3=Moderate; 4=Minor; 5=Very minor	3.35 (1.10)
Precipitation perception	Self-reported perception of precipitation changes in the last five years: 1=Extremely severe; 2=Severe; 3=Moderate; 4=Minor; 5=Very minor	3.43 (1.03)
Drought experience	1 if household experienced drought during rice production, 0 otherwise	0.10 (0.30)
Irrigation frequency	Frequency of irrigation during rice cultivation	2.84 (2.83)
Transportation	Distance to the nearest train station (km)	40.39 (41.22)

Distance to credit source	Distance to the nearest formal (e.g., bank or financial agents) and informal (e.g., relatives or friends) credit sources (km)	2.61 (2.44)
Jiangsu	1 if household locates in Jiangsu province, 0 otherwise	0.13 (0.34)
Henan	1 if household locates in Henan province, 0 otherwise	0.15 (0.36)
Hubei	1 if household locates in Hubei province, 0 otherwise	0.19 (0.39)
Hunan	1 if household locates in Hunan province, 0 otherwise	0.27 (0.45)
Sichuan	1 if household locates in Sichuan province, 0 otherwise	0.26 (0.44)
Sample size		415

Note: S.D. refers to the standard deviation.

[a] Yuan is Chinese currency (1 USD = 6.45 Yuan in 2021); 1 mu = 1/15 hectare.

Table 2 Mean differences of the selected variables between adapters and non-adapters

Variables	Adapters	Non-adapters	Mean differences
Land productivity	743.07 (719.58)	584.45 (718.04)	158.62**
Labor productivity	73.04 (217.48)	43.47 (138.61)	29.57
Age	54.17 (12.70)	53.59 (12.39)	0.58
Gender	0.68 (0.47)	0.61 (0.49)	0.07
Education	7.08 (3.82)	6.80 (4.11)	0.28
Life satisfaction	3.96 (0.91)	4.18 (0.84)	-0.23***
Family size	4.31 (1.50)	4.73 (1.57)	-0.43***
Farm size	8.97 (26.23)	7.25 (29.38)	1.72
Asset ownership	0.55 (0.50)	0.61 (0.49)	-0.06
Access to extension	0.16 (0.37)	0.26 (0.44)	-0.10**
Pest experience	0.14 (0.35)	0.09 (0.29)	0.05
Temperature perception	3.57 (0.99)	3.08 (1.17)	0.49***
Precipitation perception	3.62 (0.91)	3.19 (1.12)	0.43***
Drought experience	0.11 (0.31)	0.08 (0.27)	0.03
Irrigation frequency	2.66 (2.69)	3.06 (2.97)	-0.41
Transportation	44.76 (49.10)	35.20 (28.49)	9.56**
Distance to credit source	2.90 (2.66)	2.25 (2.11)	0.65***
Jiangsu	0.09 (0.28)	0.18 (0.38)	-0.09***
Henan	0.19 (0.39)	0.10 (0.30)	0.09***
Hubei	0.18 (0.38)	0.19 (0.40)	-0.02
Hunan	0.28 (0.45)	0.26 (0.44)	0.03
Sichuan	0.26 (0.44)	0.27 (0.44)	-0.01
Sample size	225	190	

Note: *** $p < 0.01$ and ** $p < 0.05$. Standard deviation is presented in parentheses.

Table 3 Determinants of climate change adaptation: Probit model estimates

Variables	Coefficients	Marginal effects
Age	0.015 (0.007)**	0.005 (0.002)**
Gender	0.225 (0.145)	0.078 (0.049)
Education	0.038 (0.021)*	0.013 (0.007)*
Life satisfaction	-0.260 (0.079)***	-0.090 (0.026)***
Family size	-0.072 (0.045)	-0.025 (0.015)
Farm size	0.003 (0.002)	0.001 (0.001)
Asset ownership	-0.074 (0.148)	-0.026 (0.051)
Access to extension	-0.204 (0.166)	-0.070 (0.057)
Pest experience	0.139 (0.261)	0.048 (0.090)
Temperature perception	0.213 (0.087)**	0.074 (0.030)**
Precipitation perception	0.110 (0.097)	0.038 (0.033)
Drought experience	0.069 (0.285)	0.024 (0.098)
Irrigation frequency	-0.028 (0.025)	-0.010 (0.008)
Transportation	0.005 (0.002)***	0.002 (0.001)***
Distance to credit source	0.035 (0.030)	0.012 (0.010)
Jiangsu	0.034 (0.248)	0.012 (0.085)
Henan	0.521 (0.234)**	0.180 (0.079)**
Hubei	-0.222 (0.206)	-0.076 (0.071)
Hunan	0.155 (0.185)	0.053 (0.064)
Constant	-1.098 (0.676)	
Summary statistics		
Pseudo R^2	0.121	
Model χ^2	70.83***, p-value = 0.000	
Log-likelihood	-251.477	
Sample size	415	

Note: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. The reference province is Sichuan. Robust standard errors are presented in parentheses.

Table 4 Matching quality test: balancing property

	Before matching	After matching	
		KBM	NNM (1-5)
Pseudo R^2	0.121	0.006	0.009
Mean bias	19.0	3.5	4.0
LR χ^2	69.40***	3.72	5.07
p-value	0.000	1.000	0.999

Note: *** $p < 0.01$.

Table 5 Average treatment effects of climate change adaptation on returns to land and labor: PSM estimation

	Mean outcomes			Change
	Actual	Counterfactual	ATT	(%)
KBM				
Land productivity	740.820	513.419	227.401 (72.122)***	44.29
Labor productivity	71.978	46.419	25.559 (14.964)*	55.06
NNM (1-5)				
Land productivity	740.820	524.520	216.300 (84.827)**	41.24
Labor productivity	71.978	43.966	28.013 (16.910)*	63.72

Note: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. ATT refers to average treatment effects on the treated. Bootstrap standard errors based on 100 replications are presented in parentheses for ATT.

Appendix

Table A1 Rosenbaum bounds for treatments effects of climate change adaptation on returns to land and labor

Outcome variables	Gamma	Sig+upper bound significance level	Sig- lower bound significance level	*t*-hat+upper bound Hodges-Lehman point estimate	*t*-hat+upper bound Hodges-Lehman point estimate
Land productivity	1.00	0	0	674.844	674.844
	1.20	0	0	633.333	720.000
	1.40	0	0	583.333	783.333
	1.60	0	0	550.000	836.667
	1.80	0	0	525.000	872.500
	2.00	0	0	500.000	900.000
Labor productivity	1.00	0	0	28.571	28.571
	1.20	0	0	21.875	34.722
	1.40	0	0	18.056	39.818
	1.60	0	0	14.444	46.875
	1.80	0	0	12.578	52.000
	2.00	0	0	11.638	56.250

Note: N = 225 matched pairs. Gamma is the log odds differential assignment due to unobserved factors.

Table A2 Average treatment effects of climate change adaptation on returns to land and labor: IPWRA estimation

	Mean outcomes			Change
	Actual	Counterfactual	ATT	(%)
IPWRA				
Land productivity	743.921	535.323	208.598 (69.138)***	38.97
Labor productivity	73.098	48.105	24.993 (16.022)	51.96

Note: *** $p < 0.01$. ATT refers to average treatment effects on the treated. Robust standard errors are presented in parentheses for ATT.

Table A3 Average treatment effects of climate change adaptation on net returns: PSM estimation

	ATT	
	KBM	NNM (1-5)
Net returns	318.552 (72.137)***	311.245 (94.038)***

Note: *** $p < 0.01$. ATT refers to average treatment effects on the treated. Bootstrap standard errors based on 100 replications are presented in parentheses for ATT.