

EFFECTS OF CLIMATE-SMART AGRICULTURE ADOPTION ON PERFORMANCE OF RICE FARMERS IN NORTHEAST VIETNAM

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ABSTRACT

Agricultural production is increasingly vulnerable to risks and uncertainties associated with climate changes. Climate-smart agriculture (CSA) has been proposed to address challenges in agricultural production such as food security, water shortage, drought, and soil erosion, etc. The benefits of CSA adoption for farmers have been debated. Many previous studies have indicated that impacts seem to be affected by selection bias. However, controlling such selection bias has not been considered in studies on the CSA adoption. Thus, in this study, we analyzed the impacts of CSA adoption on major economic indicators for rice farmers. The Propensity Score Matching (PSM) method was employed to address such selection bias for a case study on rice farmers in Thai Nguyen province, Vietnam. Comparing main economic indicators, we found significant differences in rice yields and used seed inputs between CSA and non-CSA adopters. Ignoring selection bias control resulted in overestimation of economic returns. The results also indicate limited contribution of CSA adoption to a reduction in pesticide and herbicide usage, and an increase in use of organic fertilizers. Some implications for further research are also discussed.

Contribution/Originality: This study is one of very few studies to have investigated the impacts of the CSA adoption on production performance of farmers while controlling for selection bias.

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1. INTRODUCTION

Climate change is a global challenge and has no borders. Global warming has been reported as the major cause leading to climate change that often has adverse effects on physical, biological, and human systems, as well as other consequences (McSweeney, Mark, & Lizcano, 2010; Nelson & Kokic, 2004). Climate change has been affecting the human life in various ways (World Bank, 2010). It is a key cause of increasing extreme weather phenomena including drought, flood, and destruction of food chains and economic resources, especially in developing countries. Impacts

related to climate change are abundant and evident in many sectors and regions such as human health, agriculture and food security, water supply, and others. Various damages related to extreme weather events are reliable indicators of the negative impacts of climate change (Patt et al., 2010). In 2018, natural disasters caused damage worth 225 billion USD globally, of which about 95% were attributed to events related to weather change (Arora, 2019). Agricultural production is highly vulnerable to climate change, which is closely linked to increases in temperature and change in rainfall, leading to considerable decrease in yield and production.

Climate change is a natural process, but the pace of this variation has significantly increased in the last 100 years. Although climate change cannot be avoided, it is necessary to seek adequate mitigation and adaptation solutions under the context of changing environment. Mitigation measures are actions taken to reduce emissions of greenhouse gases, while adaptation ones are based on reducing vulnerability to the impacts of climate change.

Vietnam is among the most vulnerable nations globally affected by climate change (Dasgupta, Laplante, Meisner, Wheeler, & Yan, 2007; MONRE, 2016). Climate change has affected many regions of Vietnam, including the Mekong River delta and the northern upland region (Ha & Duong, 2018; Ha, Nguyen, Khuat, & Nguyen, 2019). The most pressing concerns related to climate change in the northern uplands include drought in the winter, flooding in the summer, soil erosion and degradation, and changing temperature regimes such as cold spells (ISPONRE, 2009; MONRE, 2016). Agriculture is also regarded as an important source of greenhouse gas (GHG) emission after energy, accounting for about 32% of total GHG emission in Vietnam (World Bank, 2010), with the subsector of rice production contributing up to 46.3% (FAO, 2010). Recent studies have indicated that implementing climate change adaptation measures, including climate-smart agriculture (CSA) practices, could improve production efficiency, economic gains, and food security (Ho & Shimada, 2019; Khatri-Chhetri, Aggarwal, Joshi, & Vyas, 2017). According to the definition of CIAT, practices and/or technologies would be climate-smart if they could achieve at least one of the objectives of CSA (food security improvement, adaptation, and mitigation). Thus, hundreds of practices around the world are related to CSA: for instance, *smart water and irrigation management, adoption of improved crop varieties, sustainable land management, etc.* (Nguyen, Roehrig, Grosjean, Tran, & Vu, 2017).

Agriculture is generally the sector that is most sensitive and vulnerable to adverse climatic influences, especially in rice production. Limitation to accessing water constrains irrigated rice production. Shortage of water supply, water quality, and soil degradation have raised questions about the sustainability of commonly practised rice production (Bouman, Lampayan, & Tuong, 2007; Nelson et al., 2009). Thus, farmers around the world have been finding ways to cope with the adverse impacts of climate change in ensuring food security. In Vietnam, rice production plays an important role in the agriculture sector with total rice-cultivated land taking up to 67% of cropland area (GSO, 2010). Rice production has significantly contributed to food security and poverty reduction. The development of rice production has enabled Vietnam to ensure its national food security and become one of the major rice exporters in the world. Such outstanding achievements of Vietnam's rice sector have arisen from much concerted effort, including institutional reforms, application of advanced technologies and management methods in production, improved production infrastructure and irrigation systems, etc. It has become accepted among Vietnamese farmers that applying more water, seeds, and fertilizer input is the best way to increase output (Ha, 2014). However, such conventional rice production practices are encountering increasing economic and environmental costs. Moreover, increasing water shortages are constraining irrigated rice production in Vietnam, and sustainability of conventional rice production is increasingly questionable under the changing context of the environment. Thus, a number of CSA practices based on soil and water management, crop management, and adoption of improved varieties have been proposed to address those challenges. These practices have many important contributions to yield improvement, and to reduction of the impact of adverse climate change (Dung, Ho, Hiep, & Hoi, 2018; Duong & Thanh, 2019; Ho & Shimada, 2019).

In this article, CSA practices refer to the adoption of high-yielding varieties, application of the system of rice intensification (SRI), drought-tolerant varieties, and changes in planting dates. Many previous studies focused only on the impact of one adaptive measure. The impact of modern rice varieties can be found in the study of Duong and Thanh (2019), while a plethora of empirical studies have revealed comparison of the economic benefits between SRI and conventional rice practices. SRI could contribute to water saving of up to 50% and an increase in rice yield by 20-40% (Barah, 2009; Ceesay, Reid, Fernandes, & Uphoff, 2006; Kassam, Stoop, & Uphoff, 2011; Thakur, Rath, Roychowdhury, & Uphoff, 2010; Uphoff, Kassam, & Harwood, 2011). Other studies found no significant yield increase, or even a decrease, in rice productivity for SRI adopters (Dobermann, 2004; McDonald, Hobbs, & Riha, 2006; Tsujimoto, Horie, Randriamihary, Shiraiwa, & Homma, 2009). Those studies aimed to estimate the impact of only one adoption on household performance, meaning that other contributory factors were not taken into account. However, the assumption condition rarely exists in reality, which may lead to biased estimation of results. Ecological conditions may also lead to underestimation or overestimation of rice yield (Dobermann, 2004). Moreover, not only farm and farmer characteristics (Barrett, Moser, McHugh, & Barison, 2004), but also plot features may have important effects on adoption patterns and impacts (Noltze, Schwarze, & Qaim, 2012). This implies that research findings in a specific region should not be used to generalize and set up an intervention policy for other regions. Additionally, the factor of selection bias is proven to affected the output of crop production, and several different techniques have also been used to minimize its effects on estimated results for production of tea and modern rice varieties (Bac, Nanseki, & Chomei, 2019; Duong & Thanh, 2019; Tran & Goto, 2019). Although there are many studies on determinants or factors influencing farmers' adoption of CSA (Dung et al., 2018; Dung., 2019; Noltze, Schwarze, & Qaim, 2013), very few have estimated the economic impacts of this adoption. Therefore, this study was conducted to provide more insights into impact of CSA on rice production.

2. STUDY METHODS

2.1. Study Area

Northeast Vietnam consists of 9 provinces that have been much affected by climate change. Crop production plays an important role in household's livelihoods. Thai Nguyen was selected as a representative province in the region for this research. In this province, a number of CSA practices have been implemented to minimize the negative impacts of climate change, including SRI, high-yield rice varieties, and crop management practices. Based on local statistical reports and advice from leaders and staff of functional departments (including the Department of Agriculture & Rural Development, Center for Agriculture Extension, and Department of Natural Resources and Environment), two representative districts of Thai Nguyen province were selected to gather data. A total of 225 rice farmers were interviewed to collect all related information for the study, of which 11 household data that did not fit well with the objective data were excluded from the analysis. The primary data of 214 households, including 118 CSA adopters and 96 non-adopters, were used to generate results.

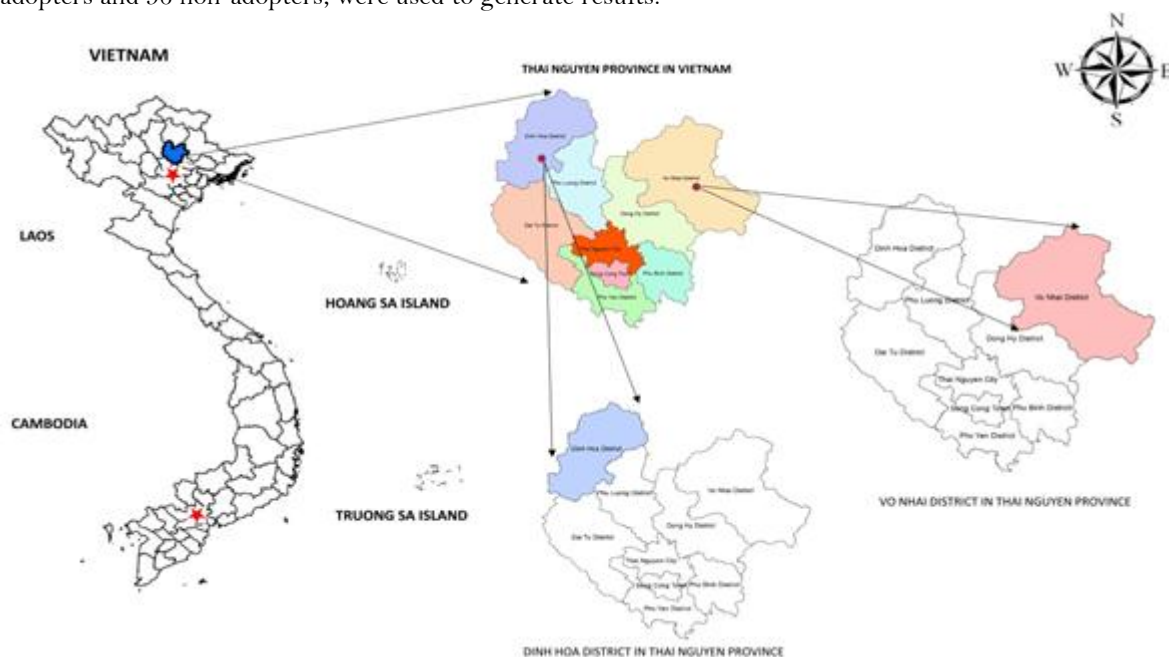


Figure-1. The study locations (Dinh Hoa and Vo Nhai districts of Thai Nguyen province).

2.2. Data Collection Methods

A range of techniques was employed to collect information on rice farmers. The techniques used included focus groups, community workshops, and structured interviews.

- Focus group discussions were undertaken to gather information on climate hazards, impacts, and adaptation practices to identify ongoing and potential CSA practices in the study area.
- Primary data collection using questionnaire was key in the study. The questionnaires used in the data survey were designed with the support and advice of local consultants and colleagues, who have extensive and in-depth experience in the area of research. Then, the questionnaire was pre-tested on 15 rice farmers in the selected study areas. Final questionnaires were completed based on the inputs and feedback of experts and research team members. All enumerators who participated in the data survey were carefully trained prior to the official survey. A random sampling method was employed to select both representative CSA adopters and non-adopters based on potential CSA practices identified as a result of focus group discussions. Finally, in-depth structured interviews were conducted to gather information from 118 adopters and 96 non-adopters between December 2019 and February 2020.

2.3. Variable Selection for Empirical Analysis

Since the study aims to evaluate the impacts of the CSA on farmers' performance, the following list of variables are used, namely:

- *Treated and untreated variables:* Adopters are defined as farmers applying at least one CSA practice (high-yielding varieties, SRI practice, crop management practices), while non-adopters are those who do not apply any of those.
- *Outcome variables:* The economic literature shows that many indicators have been used to measure outcomes from the application of technology or practices, including productivity, quantity, total value, and input factors (Amare, Asfaw, & Shiferaw, 2012; Ly, Jensen, Bruun, Rutz, & de Neergaard, 2012; Wu, Ding, Pandey, & Tao, 2010).

Table-1. Definition of variables used in the models.

Variable lists	Description	Mean (SD)
Variables used to construct propensity score		
Adoption	1 if farmer applies any CSA practices, 0 otherwise	0.55 (0.034)
Gender	1 if farmer is male, 0 otherwise	0.31 (0.032)
Education	Number of completed grades by household head	6.98 (0.187)
Labor size	Numbers of household agricultural laborers (15–60 years)	2.50 (0.073)
Irrigation	1 if farm is actively irrigated, 0 otherwise	0.67 (0.032)
Land plots	Number of cultivated land plots	3.42 (0.169)
Distance	Distance from home to farm (km)	0.79 (0.050)
Agric. credit	1 if farmer borrows agricultural loans, 0 otherwise	0.18 (0.026)
Info. access	1 if farmer is provided information on CSA, otherwise	0.39 (0.033)
Occupation	1 if farmer has main occupation in agriculture, 0 otherwise	0.93 (0.016)
Owned assets	1 if farmer has owned machines, 0 otherwise	0.96 (0.012)
Membership	1 if farmer is membership of production group, 0 otherwise	0.63 (0.033)
Land prep.	1 if farmer prepares land by machine, 0 otherwise	0.88 (0.022)
Income rate	Proportion of rice income in household total income (%)	22.65 (1.138)
Output variables used in PSM		
Total value	Total value of family's rice production (million VND)	13.28 (0.645)
Rice quantity	Total rice quantity of household (tons)	1.78 (0.086)
Productivity	Rice quantity per hectare (tons/ha)	5.23 (0.103)
Used seeds	Seed quantity used (kg)	13.94 (0.635)
Manure	Farmyard manure used in rice fields (tons)	0.43 (0.070)
Fertilizers	Chemical fertilizer used in rice fields (tons)	0.34 (0.016)
Pesticide cost	Pesticide cost in rice fields (million VND)	0.45 (0.035)
Work days	Number of working days in rice fields per year	20.98 (1.099)
Other costs	Expenditures on other inputs (million VND)	3.27 (0.221)

The list of variables used to estimate the propensity scores was compiled on the basis of economic theory, the literature, and the actual status of rice production in the study area (Khandker, Koolwal, & Samad, 2010; Smith & Todd, 2005). Previous studies have extensively documented the fact that these variables should cover (1) the characteristics of household head (gender, formal education); (2) household demographic and socioeconomic factors (number of agricultural laborers, main occupation, access to credit sources, agricultural services, off-farm employment, method of land preparation, status of owned machine, member of production group, rate of rice income); and (3) area characteristics (irrigation, home–farm distance, plot number) (Kassie, Shiferaw, & Muricho, 2011; Mason & Smale, 2013; Matuschke & Qaim, 2009; Mendola, 2007).

2.4. Data Analysis

The collected data were checked prior to statistical analysis to ensure accuracy. In case the collected information and data were not consistent, farmers were contacted for further interview. Unreliable data were omitted from analysis.

Economic achievements have generally been driven by related development policy, technological advances, and support programs, briefly termed interventions. Evaluation of impact from such interventions has received much attention from researchers for over a decade. Many approaches and econometric methods have been employed to impact evaluation (Khandker et al., 2010). Application of a specific technique is always debated in empirical economic studies (Wang, Moustier, & Loc, 2014). The treatment effect could be measured by coefficients of a regression model (Imbens, 2004), while a dummy variable is used to estimate impacts. The best output of impact evaluation can be generated if the original difference does not exist in the estimation. In other words, the same farmers should be compared with each other before and after an intervention. This could easily be done in the research trial with small samples, but it would appear impossible at the regional scale. Previous studies found that characteristics of individuals have significant effects on their performance rather than interventions (Imbens & Wooldridge, 2009). Another important factor that might lead to biased estimation is that datasets are often gathered from non-randomized studies rather than randomized trials (Becker & Ichino, 2002). To estimate causality, such a self-selection issue needs to be overcome in treatment status.

In the economic literature, the PSM technique has frequently been applied to control selection bias associated with observable variables (Rosenbaum & Rubin, 1983; Takahashi & Barrett, 2014). The counterfactual is constructed by matching observations with other treatments using their propensity scores. The treatment effect is estimated by measuring the output difference of the matched observations. PSM is a mathematical procedure used to estimate average treatment effects on the treated (ATT) (Becker & Ichino, 2002). The observation propensity score is first estimated using a logit regression model, as in Equation 1:

$$\mathcal{Y}(1,0) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n \quad (1)$$

where \mathcal{Y} denotes the dependent variable (1 implies CSA adopters, 0 for non-adopters), β are the estimated coefficients and X_n denotes covariates described in Table 1.

Secondly, the nearest-neighbor matching technique is applied to match similar observations using propensity scores estimated by the logit model. Kernel and radius matching techniques are also used to avoid bad matches. In addition, we employed matching with replacement to increase cross-checking. In the second step, the estimates of ATTs for the outcome variables are undertaken following Equation 2:

$$E(\mathcal{Y}(1) - \mathcal{Y}(0) | D_i = 1) = E(\mathcal{Y}(1) | D_i = 1) - E(\mathcal{Y}(0) | D_i = 1) \quad (2)$$

With a particular observation i and outcome \mathcal{Y} , D_i denotes the treatment status ($D_i = 1$ for treatment; $D_i = 0$ for control). $\mathcal{Y}(1)$ is the outcome of treatment while $\mathcal{Y}(0)$ is the outcome of control status. The term $E(\mathcal{Y}(1) | D_i = 1)$ is an average outcome of treated groups, and the term $E(\mathcal{Y}(0) | D_i = 1)$ is an average outcome of the matched control group. The standard errors of the ATT are also computed for statistical tests following Abadie & Imbens (2016). Several statistical indicators must be estimated to test matching quality. Matching quality is considered to be good enough if significant differences do not exist systematically after matching based on the propensity score (Caliendo & Kopeinig, 2008). Moreover, lower standardized bias should be created after matching (Rosenbaum & Rubin, 1985). Additionally, the likelihood ratio test and pseudo- R^2 indicators should also be included for checking. The matching is good if the likelihood ratio test is not statistically significant (Smith & Todd, 2005), and pseudo- R^2 should be fairly low (Sianesi, 2004). Finally, the condition of common support should also be tested carefully by visual inspection of the densities of propensity scores of treated and untreated groups. Observations outside the support region should be removed in effect estimation (Caliendo & Kopeinig, 2008).

3. RESULTS AND DISCUSSION

3.1. Descriptive Results

Table 1 presents descriptive statistics for the variables used in the models. It shows that CSA farmers account for 55% of the total sample. The results of t -tests for mean differences of covariates and outcome variables between treatment and control groups are reported in Tables 2 and 3. A substantial imbalance exists among selected covariates, implying the existence of self-selection issues. Households in the treatment group have higher numbers of headed males, and household heads are more highly educated than those in the control group. Notably, members of the treatment group often have more access to extension services through training courses on CSA compared to control group members. Moreover, there are also significantly positive differences in owed machinery and credit loans, suggesting that rice households following CSA may have been initially wealthier than other households. Another explanation is that some credit loans may have been used to invest in agricultural machinery and high-yielding varieties. In addition to observed covariates, there may be unobserved covariates that have significant impacts on outcome variables, such as yield: for example, household motivation could not be observed. Motivated households are more likely to apply CSA practices in the field and, as a result, their production performance might be better than those with less motivation. Advanced education and technical knowledge, which can have positive impacts on both CSA adoption and farm performance, also cannot be quantified easily.

In regard to outcome variables, the CSA farmer group reported significantly higher mean values than the non-CSA farmer group on gross revenue, rice yield, and rice quantity. CSA households' gross revenue of rice production was nearly 30% higher than that of non-adopted ones. Similarly, rice yield and quantity were significantly higher for the treatment group. Tables 2 and 3 also reveal the mean differences in other variables related to production inputs of rice farming. While seed quantity and labor days are significantly less used for farm systems applying CSA practices, other costs are more highly spent for conventional farming ones.

As mentioned above, the difference in outcome variables may be derived from the initial imbalance of observed and unobserved covariates between treated and untreated farmers, rather than the effects of CSA practices. In other words, there might be biased conclusions on treatment effects if studies used only simple mean comparisons of outcome variables between two groups. Thus, it is important to control self-selection in this study.

Table 2. Mean differences of variables used to construct propensity scores.

Covariates	CSA adopters		CSA non-adopters		Diff.	
	Mean	S.D	Mean	S.D	Mean	S.E
Gender	0.373	0.045	0.229	0.043	0.143**	0.062
Education	7.492	0.243	6.343	0.278	1.145***	0.369
Labor size	2.441	0.093	2.583	0.119	-0.143	0.151
Irrigation	0.661	0.044	0.698	0.047	-0.037	0.064
Land plots	3.373	0.241	3.479	0.236	-0.106	0.338
Distance	0.746	0.061	0.858	0.083	-0.117	0.103
Agric. credit	0.220	0.038	0.125	0.034	0.095*	0.051
Info. access	0.534	0.046	0.219	0.042	0.315***	0.063
Occupation	0.979	0.015	0.898	0.028	0.081**	0.031
Owned assets	0.932	0.023	0.823	0.042	0.109**	0.048
Membership	0.644	0.044	0.614	0.049	0.029	0.067
Land prep.	0.966	0.017	0.958	0.021	0.008	0.026
Income rate	24.478	1.545	20.423	1.664	4.055*	2.271

Note: * 10% significance level; ** 5% significance level; *** 1% significance level

Source: Authors' survey data 2019–2020.

Table-3. Mean differences of variables used to estimate rice performance.

Outcome variables	CSA adopters		Non-CSA adopters		Diff.	
	Mean	S.D	Mean	S.D	Mean	S.E
Total value	15.348	1.026	10.746	0.605	4.602^{***}	1.191
Productivity	5.751	0.129	4.605	0.142	1.145^{***}	0.192
Rice quantity	2.049	0.135	1.458	0.083	0.592^{***}	0.158
Used seeds	12.694	0.865	15.480	0.915	-2.786^{**}	1.260
Manure	0.511	0.111	0.349	0.076	0.162	0.134
Fertilizers	0.340	0.023	0.339	0.022	0.001	0.031
Pesticide cost	0.429	0.042	0.484	0.059	-0.056	0.072
Labor days	18.87	1.526	23.57	1.54	-4.698^{**}	2.171
Other costs	1.319	0.225	1.254	0.241	0.066	0.329

Note: * 10% significance level; ** 5% significance level; *** 1% significance level

3.2. Determinants of CSA Adoption

Table 4 presents parameter estimates of a logit model equivalent to the first stage of the treatment effect model. Although the main objective of the study was to assess the effect of CSA adoption, logit estimation also reveals some interesting findings. The results indicate that some factors have positive impacts on the adoption of CSA practices, including gender, formal education, main occupation, irrigated farms, access to extension services, methods of land preparation, credit loans, and rate of rice income. Among these, formal education of household head, rate of rice income, and access to extension training had statistically significant impacts on household adoption decision making. The positive and significant coefficients show that formal education, rate of rice income, and technical training are very important in adoption whereas positive and insignificant signs show no important impact on adoption decision. Other covariates have negative impacts on household adoption decision but have no statistical significance.

Table-4. Propensity score for CSA adoption.

Covariates	Coeff.	St. err
Gender	0.425	0.345
Education	0.130	0.061 ^{**}
Labor size	-0.013	0.153
Occupation	1.228	0.851
Land plot	-0.028	0.066
Distance	-0.076	0.219
Info. access	1.139	0.345 ^{***}
Irrigation	0.337	0.338
Land prep.	0.782	0.487
Membership	-0.193	0.326
Agric. credit	0.632	0.426
Income rate	0.012	0.009 [*]
Owned assets	0.135	0.928
_cons	-0.500	1.450

Note: * 10% significance level; ** 5% significance level; *** 1% significance level.

3.3. Rice Yield and Economic Indicators

As described in section 2.4, better farm performance, such as rice yield and economic indicators, could have been under- or overestimated due to the consequence of selection bias. Thus, before examining the casual effects of CSA adoption using PSM, it is important to discuss matching quality using different techniques. First, balancing the condition of all selected covariates between adopter and non-adopters needs to be satisfied. Table 5 reports the results of testing balance conditions. There is no significant difference in the propensity score after matching. Moreover, significantly lower standardized bias was created, as shown in Table 6. Before matching, the mean standardized difference for overall covariates used to construct the propensity score was about 23.8, but this was markedly reduced to 5.6 after matching. Additionally, there are many selected covariates with an absolute value of percentage of bias that >20 before matching, but these all reduced to <20 after matching (Figure 2). All these signals indicate very good balancing propensity (Caliendo & Kopeinig, 2008; Rosenbaum & Rubin, 1985; Sianesi, 2004). Second, another important requirement is to check the condition of common support regions when the matching procedure is performed. According to Khandker et al. (2010), the effectiveness of PSM depends on having a large number of treated and untreated observations. Figure 3 shows that few CSA adopters with propensity score greater than the maximum or lower than minimum of non-adopters fall out of the common support region. In short, both balancing and common support conditions are very adequate in this study.

Table-5. Balance checking after matching: CSA adopters and non-adopters.

Covariates	Mean		% bias	P-value
	CSA adopters	CSA non-adopters		
Gender	0.187	0.229	-9.2	0.480
Education	6.489	6.343	5.4	0.685
Labor size	2.781	2.583	18.1	0.239
Occupation	0.979	0.979	0.0	1.000
Land plot	3.379	3.479	0.0	1.000
Distance	0.882	0.858	3.3	0.819
Info. access	0.229	0.218	2.3	0.863
Irrigation	0.708	0.698	2.2	0.875
Land prep.	0.843	0.822	6.1	0.711
Membership	0.552	0.614	-12.9	0.382
Agric. credit	0.104	0.125	-5.5	0.652
Income rate	20.78	20.42	2.2	0.877
Owned assets	0.947	0.955	-5.4	0.734

Mean standardized difference before and after: 23.8 and 5.6, respectively

Table-6. Results of matching quality.

Matching techniques	Pseudo- R^2		LR χ^2 (P-value)	
	Before	After	Before	After
NNM	0.145	0.016	42.70***	4.34
Radius	0.145	0.011	42.70***	2.41
Kernel	0.145	0.006	42.70***	1.43

Note: *** 1% significance level. Source: authors' survey data 2019–2020.

NNM: Nearest-neighbor matching; Kernel: Matching with default bandwidth = 0.06; Radius: Matching with caliper = 0.05.

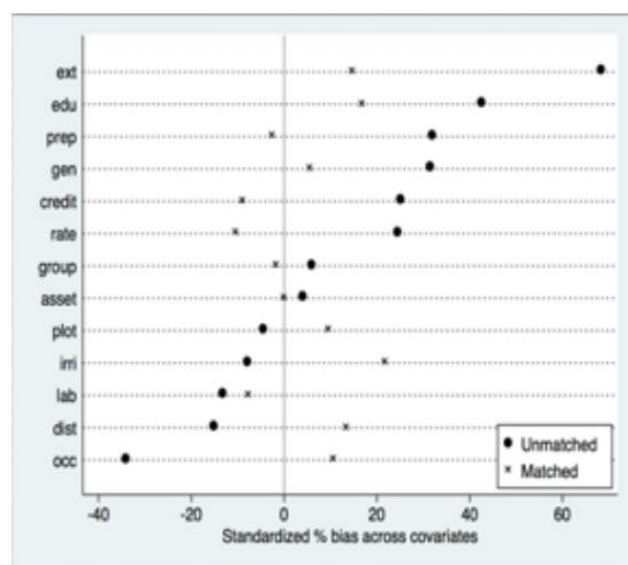


Figure-2. Distribution of % bias across covariates.

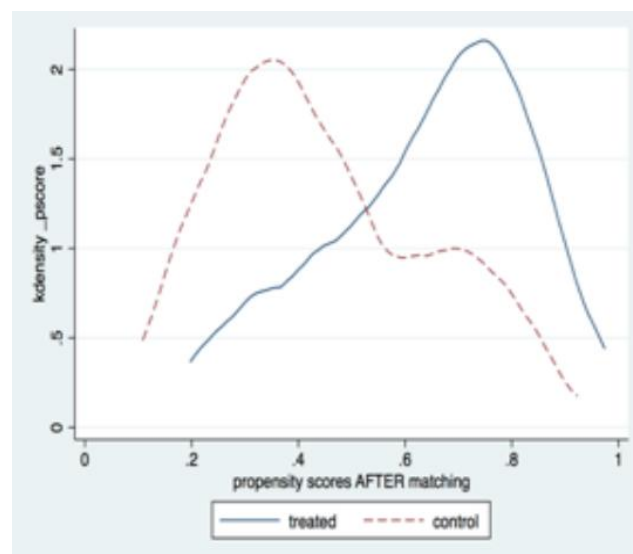


Figure-3. Density distribution of propensity score.

Table-7. Average treatment effects of CSA adoption on production performance.

	NNM		Radius		Kernel	
	ATT	S.E	ATT	S.E	ATT	S.E
Total value	3.340**	1.462	3.212*	1.239	3.911**	1.345
Rice quantity	0.501**	0.198	0.375**	0.170	0.532***	0.178
Productivity	0.715**	0.282	1.061***	0.245	0.954***	0.246
Seed quantity	-3.583**	1.789	-5.364***	1.655	-3.399**	1.591
Farmyard manure	0.288	0.202	0.119	0.153	0.274*	0.156
Chem. fertilizers	-0.028	0.048	-0.045	0.042	0.006	0.038
Pesticide cost	-0.152	0.144	-0.196	0.107	-0.155	0.096
Work days	-1.477	2.876	-3.786	2.671	-2.223	2.728
Other costs	-0.143	0.591	-0.631	0.522	-0.183	0.521

Note: * 10% significance level; ** 5% significance level; *** 1% significance level.

NNM: $n = 1$; Kernel = 0.06; Radius = 0.05

The empirical analysis used various matching techniques, including nearest neighbor, radius and kernel matching. The estimation results for the whole observations are presented in Table 7. These results are consistent across different matching methods. CSA adoption clearly had positive effects on household farming performance. First, CSA adoption improved farmers' total value of rice production because it resulted in a higher rice yield. More specifically, total value increased significantly, by approximately 3.2–3.9 million VND, which is equivalent to a 26.7% increase compared to the control group. Similarly, there was increase in rice yield across matching techniques, and all have statistical significances at 5%. The study also indicates strong evidence of higher productivity for farmers adopting CSA practices. Average rice productivity was significantly improved, by approximately 0.7–1.1 tons, representing a relative increase of about 14–21% higher than that of the non-adopters. In addition, CSA farmers could reduce seed input although the decreased magnitude of spent seed differs across matching techniques. Seed quantity was significantly reduced, by approximately 3.6–5.4 kg, equivalent to 22–31.5% compared to conventional farmers. Other inputs of rice production, including farmyard manure, chemical fertilizers, pesticide costs, labor days, and other expenses, do not have statistically significant differences for the treated group. In this study, net income of rice production was not estimated because rice production is mostly used for family demand rather than market sales. In the field survey, respondents said that rice production is primarily spent for daily food consumption and partly used for feeding animals, while cash income mainly comes from off-farm jobs. Thus, this can partly affect household time and money investment in rice production.

3.4. Discussion

Our results indicate that rice farmers received positive and significant economic impacts from applying CSA practices. Although several studies have reported that CSA adoption has positive impacts on economic returns, the issue of selection bias has been ignored in evaluation. Thus, our study has contributed to the evaluation literature on the economic impact of CSA practices. Our findings also reconfirmed that the adoption of CSA practices has positive effects on economic returns. Nevertheless, this could have been overestimated if selection bias was not controlled in the study. The positive effects on rice productivity are consistent with previous findings on the effects of SRI adoption (Castillo, Minh, & Pfeifer, 2012; Thakur et al., 2010), but the results are also contradictory to several studies (Dobermann, 2004; McDonald et al., 2006; Tsujimoto et al., 2009). We also found a positive impact of CSA application on total value. This finding could be easily understood due to an increase in rice productivity. Higher total value was also reported in several studies on the effects of the adoption of SRI practice or sustainable agricultural technologies (Noltze et al., 2013; Tuyet, Fry, Van Hoang, & Ha, 2017). Our study also compared inputs used and costs between CSA and non-CSA farmers. As expected, seed quantity was much less for CSA farmers, contributing to a decrease in their total variable costs. This is because many rice farmers apply SRI practices in their field – known as the use of single seeding and wider planting density. This finding is also in line with previous studies (Noltze et al., 2013; Tuyet et al., 2017). The use of other inputs, including chemical fertilizers, pesticides and labor, was also slightly lower on CSA farms, while the use of organic fertilizers and manure was slightly higher. However, these did not differ significantly on any variables. Remarkably, regular weeding, organic fertilizers, and farmyard manure are encouraged with CSA practices. However, farmers still use herbicides for weeding in practice. Similarly, fertilizer application was also not statistically different. The difference with CSA farmers was that they applied more balanced proportions of different fertilizers. Our in-depth interviews with rice farmers in the field survey also indicated that income from rice production accounts for only a small proportion of total household income sources. Farmers often apply chemical fertilizers and herbicides in weeding for time saving and convenience. The time thus saved is spent on off-farm activities for additional income. In addition, farmers commonly exchange labor with neighbors during the rice transplantation period. Hired labor is involved only in rice harvesting, and is computed in other costs. These cost patterns are not different between CSA adopter and non-adopter groups.

4. CONCLUSIONS

This study analyzed the effect of CSA in Northeast Vietnam. The original data from 214 small-scale rice farmers were used to estimate the impact of this adoption on farm economic indicators. A logistic regression model was applied to determine the factors affecting household adoption decisions in the first stage, while PSM was employed to estimate ATT in the following step. We carefully checked both balance and common support conditions to ensure good matching quality after the matching process. In other words, selection bias was minimized as much as possible in our study.

The study findings showed that there are many important determinants motivating households to adopt CSA in rice production. Of these, formal education of household heads, access to extension services, and rate of rice income are key contributing factors. This implies that expansion of CSA practices would be more successful if these factors are improved, especially in providing regular information on CSA through training courses, because this still is a key information channel for farmers in the research area.

If the issue of selection bias is not controlled, simple comparison would have resulted in overestimation of economic indicators in the study. Our findings indicated that farmers are able to achieve higher average yield by applying CSA practices in rice production. As a result, this would lead to higher quantity and total value of rice production for local farmers. Our finding also reconfirmed a significant increase in rice quantity and total value for CSA adopters compared to non-adopters. Moreover, adoption has a clear impact on reduction of seed input in rice cultivation. Farmyard manure is used slightly more in CSA farms, while other variable inputs such chemical fertilizers, pesticide costs, labor, and other costs did not have significant influence.

Although the study has provided clear evidence on the positive impacts of CSA adoption on rice yield, other aspects such as environmental protection and agro-ecological conservation have not been achieved as expected. Thus, additional and suitable policies are needed to encourage higher application levels of organic fertilizers, and minimization of the use of synthetic pesticides and herbicides.

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