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Do Improved Cropping Patterns Increase Income of Farmers in the Sandy Area of Hai Lang District?

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Abstract. Crop production in the sandy area of Hai Lang district is transforming, shifting from traditional mono-cropping models to improved cropping patterns such as annual intercropping, annual crop rotation, and mixed patterns of intercropping and rotation. This study estimated the income effect of the adoption of improved cropping patterns, using primary data collected from a sample survey of 186 households from two selected communes in a sandy area of the district. It was found that farmers' likelihood of adoption of improved cropping patterns is significantly affected by the age of the household head, the household's wealth status, the plot area, participation in extension training, and access to credit. Using the propensity score matching approach, the income effect of adoption was estimated. The adopters at the study site attained income that is 20–25% greater than matched non-adopters.

Keywords: cropping pattern, adoption, sandy area, household income

1 Introduction

A cropping pattern refers to the way different crops are grown and managed on the same piece of land over a certain period. It shows how farmers plan the timing, arrangement, and combination of crops to make the most of their resources. In short, it is about choosing crops to grow, when to grow, and how to grow. Meanwhile, improved cropping patterns (ICPs) refer to changes in the way crops are grown on a farm, involving strategic combinations of crops, either together or in a sequence, to enhance overall productivity, resource utilization, and sustainability of agricultural systems. This can include crop rotation, intercropping, relay cropping, and cover cropping, all aiming to optimize land use, reduce soil degradation, and increase yields. With the goal of increasing yield, improving soil health, and reducing environmental impact ICPs typically involve moving away from monoculture (growing a single crop) to more diverse systems [1].

Factors that motivate farmers to improve their cultivation patterns are various, including economic incentives, environmental concerns, and social pressures. Economic factors such as increased profitability and market demand, along with the potential for higher yields and reduced costs, can incentivize farmers to adopt new technologies and practices. In many cases, innovative practices are induced by consumers' increasing demand for sustainable and high-quality products. Environmental awareness and a desire to minimize the negative impact of agriculture on the ecosystem also play a role. Climate change is impacting agricultural production, and farmers are looking for ways to make their cropping patterns become more resilient to changing climate with more hazards such as drought, storms, and floods. In short, farmers are motivated to innovate by a complex interplay of economic, environmental, and social factors. Understanding these motivations is crucial for developing effective policies and programs that can promote sustainable and innovative agricultural practices [2].

Although improvements of cropping patterns are context-specific and differ across regions and groups of farmers, there is a trend toward growing more high-value crops such as fruit and vegetables and opting for crops that require less water, particularly in areas facing water scarcity. With ICPs, environmental and sustainable practices are adopted to minimize soil disturbance and the use of chemicals. In many cases, ICPs come alongside the adoption of high technologies, including precision agriculture, advanced irrigation systems, and the development of high-yielding crop varieties, and these changes can significantly boost agricultural productivity and efficiency [3].

Hai Lang, a coastal district in the Central Coast of Vietnam, borders the sea to the east. The district is about 12 km south of Dong Ha city and 55 km north of Hue city. The terrain of the district from east to west is sandy area, plain area, and mountainous area, respectively. Its total area is nearly 43,000ha of which the mountainous area accounts for 55%, the delta for 32%, and the sandy area for the remaining 13%. It was estimated that 48% of the district's land area is highly degraded [4]. Sandy soil with low fertility and multiple climatic hazards such as severe drought, hot wind, storm, and floods are the distinctive features that hinder agricultural production of the district's coastal area [5].

In the sandy areas of Hai Lang district, prevailing agricultural crops in the district include cassava, maize, potato, rice, etc. In the past, the traditional cropping patterns were basically monocropping, planting a single crop such as cassava, sweet potato, rice, or chives in the same field for years. This type of monoculture has significant drawbacks, including soil degradation and increased vulnerability to pests and diseases. The last decade observed a remarkable change in the district; the traditional mono-cropping patterns were replaced with ICPs such as diversified crop rotation and intercropping models. The typical ICPs in the district's sandy area include intercropping of annual crops, annual crop rotation, and mixed patterns of intercropping and rotation.

The intercropping pattern grows cassava and chives in association. Chives are planted in October, and leaf harvest is in November, and bulb harvest in April; cassava is planted in October on the two edges of the chives bed and harvested in June. Rice straw is used as a mulching material, and manure is applied to manage soil nutrients.

The annual crop rotation includes annual crops such as green beans and bitter melon. They are planted on furrows in sequence over growing seasons; green beans are planted in January and harvested in May, and bitter melon is planted in August and harvested in November. Green beans, a drought-tolerant plant, can grow well in poor, sandy land in coastal areas, and as a nitrogen-fixing plant, it can improve soil fertility.

The mixed pattern is a rotation of two intercropping patterns. Maize is intercropped with green beans in the period from January to May, and maize is intercropped with peanuts from June to October. In this pattern, beans and peanuts, nitrogen-fixing crops, can improve soil fertility and prevent pests. The following period is from November to December, the rest time for the soil to regain productivity.

Recently, impact evaluation of changes such as innovation adoption has been indispensable for program and policy formulation and adjustments. An impact evaluation helps to make valid attribution as it identifies and tests the cause-and-effect relationship associated with the changes [6–8]. In agriculture, income impact evaluation is often used to provide reliable evidence on the contribution of a change in production practices to farmers' income. The adoption of ICPs has been recognized by farmers and policymakers as one of the key strategies to increase income, soil fertility, sustainability, and resilience of agricultural production. However, the adoption of ICPs remains limited, and monoculture, degrading farming practices are still prevailing in many places [9]. In connection with what has been discussed above, as a contribution to gaining a comprehensive insight into agricultural innovations. This empirical study was designed to shed a light on the income effect of ICPs on farm households in the sandy area of Hai Lang district and to provide relevant policy implications.

2 Research Methods

2.1 Data Collection

Data for this study were collected from a sample survey of 186 farm households (Table 1) in two communes, Hai Ba and Hai Duong, in the sandy area of Hai Lang district. The choice of communes was made based on several considerations, including agricultural land use, cropping patterns, and other natural and socio-economic characteristics, to ensure that they are good representatives for the study sites. Households with and without adoption of the ICPs were randomly selected from lists of households provided by the communes. Direct interviews with household heads were carried out using questionnaires to collect information on the farm households' socio-economic and demographic characteristics and their coping patterns.

In addition, a focus group discussion with the participation of 8 farmers including adopters

Table 1. Number of interviewed farm households

Communes	All	Adopter	Non-adopter
Hai Ba	89	42	47
Hai Duong	97	45	52
Total	186	87	99

Source: Household survey

and non-adopters were organized in each of the two communes, Hai Ba and Hai Duong. Issues related to ICP adoption such as technical requirements, affordability, profitability and considerations of other difficulties and opportunities.

2.2 Income Effect Evaluation Using Propensity Score Matching (PSM)

Methods to evaluate impact are classified into three groups: experimental, quasi-experimental, and non-experimental designs. Quasi-experimental designs are now increasingly used in impact evaluation, especially when a control group is difficult. The three methods that quasi-experimental designs use to construct comparison groups are regression discontinuity, propensity score matching (PSM), and difference in difference. When being treated or participating in a program is voluntary, quasi-experimental designs use PSM to construct comparison groups. People are matched on factors that affect their tendency to participate/adopt. PSM helps to avoid selection bias when collected data of a comparison group is not representative. Given the fact that adoption of ICPs is voluntary and the cross-section data available, this study uses the PSM method.

The logistic model for propensity score estimation

The PSM method estimates the probability of participating in a program, using a logit model with observed characteristics. The estimated probabilities, or propensity scores, are then used to match participants to nonparticipants to form matched sets of treated/participant and untreated/nonparticipant subjects who share a similar value of the propensity score [10].

Following Ben-Akiva and Lerman [11] and Judge et al. [12], with two choices (adoption and non-adoption), a binary logit model was constructed to estimate the probability that a farmer would adopt ICPs. Then the probability of farmer n choosing alternative i is given by

$$P_n(i = 1) = \frac{e^{\mu V_{in}}}{e^{\mu V_{in}} + e^{\mu V_{jn}}} = \frac{1}{1+e^{-\mu(V_{in}-V_{jn})}} \quad (1)$$

$= \emptyset(V)$

$= \emptyset(\beta' x),$

Where $\mu > 0$ is the scale parameter, assumed equal to one; V_{in} and V_{jn} are the deterministic portion of utility (to be maximized); i = 1 adopting ICP and j = 0 not adopting ICP. It means that Prob (Adoption) = $\phi(\beta'x)$ where $\beta'x$ is the vector of parameters to be estimated, and x is the vector of observations.

The reduced form of the logit model in this study is as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \tag{2}$$

The dependent variable (Y) in the model is the adoption status of farm households (taking a value of 1 if the farmer adopted ICP and 0 if the farmer did not adopt). X_k are household characteristics, which are defined in Table 2. They include the characteristics of household head (gender, age, and education), household assets (economic status, labor, and land), and the institutional context (training/extension, credit access, and commune dummy). It was well-established in innovation adoption literature that these groups of variables may influence the adoption of ICPs and help explain the observed differences in adoption behavior across households. Household head characteristics (gender, age, and education) affect awareness and openness to the adoption of ICPs. Household assets (economic status, labor, and land) indicate the available production resources to implement changes. Institutional factors (training, credit access, commune) represent external support that can facilitate adoption.

Table 2. Independent variables used in the IPC adoption model

Variable names	Description	Values
Gender	Gender of household head	= 1 for male, = 0 for female
Age	Age of household head	Years
Education	Education of household head	Years in school
Poverty	Wealth rank of households	= 1 for poor household, = 0 for otherwise
Agricultural labor	No. of agricultural laborers	Number of laborers
Number of plots	Land plots of a household	Number of land plots
Plot area	Area of the surveyed plot	ha
Training on ICP	Participating in training on ICP	= 1 participation, = 0 non-participation
Access to credit	Credit access to farm household	= 1 with credit access, = 0 without access
Hai Ba	Household in Hai Ba commune	= 1 in Hai Ba commune, = 0 otherwise

Source: Household survey

Matching methods and estimating the income effect

The most common matching methods, Nearest, Radius, and Kernel, were used to construct comparison groups: treated/adopter and untreated/non-adopter. The mean outcome/income of treated and untreated subjects in the matched sample was estimated, and the income effect of ICP adoption is the difference between the mean outcome of the two groups, treated and untreated.

Given a sample of farmers and sustainable land management, each farmer has only two potential outcomes: $Y_i(0)$, the outcomes under the control treatment (not adopting the ICP), and $Y_i(1)$, the active treatment (adopting the ICP). Each farmer can get either one of the two outcomes. Let T be a dummy variable denoting the treatment received (T = 0 for control treatment and T = 1 for active treatment). Thus, only one outcome, $Y_i\,(Y_i = Z_i, Y_i(l) + (1 - T_i)Y_i\,(0))$, is observed for each farmer: the outcome under the actual treatment received.

For each farmer, the effect of the program is the difference between the two outcomes, $Y_i(1) - Y_i\,(0)$. The average treatment effect (ATE) is defined to be $E[Y_i\,(1) - Y_i\,(0)]$. The ATE is the average effect, at the population level, of moving an entire population from untreated groups to treated ones. Another measure of treatment effect is the average treatment effect for the treated (ATT). The ATT is defined as $E[Y(1) - Y(0) \mid Z = 1]$. The ATT is the average effect of treatment on those subjects who ultimately received the treatment [13].

3 Study results

3.1 Characteristics of Surveyed Households

Characteristics of households surveyed are presented in Table 3. On the whole, on average, the household heads were 46 years of age and had 6.7 years of schooling. Each household had about 2 agricultural laborers and 3 plots of agricultural land. The average annual income of all surveyed households was VND 64 billion. The percentage of poor households in the sample was 14%, and about one-third of the survey households had access to credit. The households that participated in training on ICPs by the extension staff accounted for 58% of the sample.

The two groups, adopter and non-adopter households, differ from each other significantly in several aspects. The percentage of male household heads in the adopter group is higher than in the non-adopter groups. The difference in income and poverty rate was statistically significant at 0.01 and 0.05 levels, respectively. The area of plots with IPC is significantly larger than plots with mono-cropping patterns. The adopter group has higher access to credit and training on ICP. However, they are similar in terms of age and educational attainment of household head, number of family laborers, and agricultural land plot.

Table 3. Characteristics of IPC adopting and non-adopting households

Variable name	All sample	Adopters	Non-adopters	Difference	
Gender	0.57	0.63	0.52	0.11	**
Age	46.47	45.60	47.30	-1.70	ns
Education	6.70	6.90	6.50	0.40	ns
Income	63,706.64	69,052.98	58,585.41	10,467.57	***
Poverty	0.14	0.11	0.17	-0.06	**
Agricultural labor	2.25	2.27	2.24	0.03	ns
Number of plots	3.15	3.20	3.10	0.10	ns
Plot area	0.46	0.55	0.37	0.18	***
Training on ICP	0.58	0.75	0.41	0.34	***
Access to credit	0.35	0.46	0.25	0.21	***
Hai Ba commune	0.48	0.48	0.47	0.01	ns

Source: Household survey

Note: ***, ** statistically significant at 0.01 and 0.05 levels respectively

ns non-statistically significant

3.2 Estimates of Adoption Model

Table 4 shows the estimates of the binary logistic model. With a chi-square test statistic of 117.152, the model is statistically significant in explaining farmers' decision to adopt ICPs. The coefficients and marginal effects of the independent variables such as gender of the household head, poverty, plot area, training on ICP, and access to credit are statistically significant. This implies that those variables significantly affect variation in the probability of a household adopting ICPs. Meanwhile, education level and age of household head, number of agricultural laborers and land plot are not statistically significant in explaining the adoption decision of survey households.

The gender of household heads significantly affects ICP adoption; the probability of adopting ICPs is 0.1647 higher if the household heads are male. As indicated by the negative and statistically significant coefficient of the poverty dummy, poor households may not be able to afford to adopt costly ICPs. The poverty dummy variable has a negative and statistically significant coefficient; this indicates that poverty makes poor households unable to afford the adoption of costly ICPs. If a household got out of poverty, its probability to adopt ICPs could increase by 0.0352. The likelihood of adopting ICPs is higher for plots with larger areas. A possible explanation is that adoption of ICPs is more cost-effective with larger plots. A similar finding was reported by Shively [14], that plot characteristics influenced a farmer's choice of land use practices. Participation in ICP training could increase a household's probability to adopt ICPs by

0.2640, as training on ICPs helps farmers have better knowledge and skills to adopt. Wu et al. [15] also found that technical knowledge that farmers could attain through extension services enhanced the adoption of sustainable agriculture. The variable access to credit has a positive and statistically significant impact on adoption. It could increase the probability of farm households adopting ICPs by 0.2856. This is due to a possible reason that access to credit alleviates a household's financial constraint, making it able to afford ICP adoption. The coefficient of the commune dummy, Hai Ba, is not statistically significant. This variation may be due to the high homogeneity of communes in the sandy area.

Table 4. Results of logistic regression on the ICP adoption

Variables	Coefficients		Marginal effects
Gender	0.2211	**	0.1647
Age	-0.0019	ns	-0.0005
Education	0.0064	ns	0.0023
Poverty	-0.1013	**	-0.0352
Agricultural labor	0.1245	ns	-0.0664
Number of plots	-0.2299	ns	-0.0402
Plot area	0.0115	**	0.0647
Training on ICP	1.1323	***	0.2640
Access to credit	0.9267	***	0.2856
Hai Ba	0.6763	ns	0.1690
Constant	0.3659	ns	
Log Likelihood			-407.632
LR Chi^2			117.152
Prob > Chi^2			0.000
Pseudo R^2			0.136

Note: ***, ** statistically significant at 0.01 and 0.05 levels respectively; ns non-statistically significant

3.3 Income Effect of ICP Adoption

The propensity score of each farm household was estimated using the results of the logistic regression and observed characteristics of the surveyed households. The comparison groups were constructed by three matching methods, the Nearest, Radius, and Kernel. Tests for balance between the groups were conducted to ensure that the estimated treatment effect is not driven by differences in observed characteristics between the groups, but rather by the treatment itself. It was found that the distributions of the covariates used to create propensity scores are similar across both groups. This means that treated and control groups are comparable after matching.

Table 5 shows the income effect of ICP adoption. The results are similar for the three matching methods (the Nearest, Radius, and Kernel). It was established in the current study that for the surveyed farms, the average income of adopter households (ATT) is significantly higher than that of matched non-adopter households. This is similar to findings reported by Wu et al. [15].

The present study found that the annual income of ICP adopter households ranged from VND 68.8 to 69.4 million and that of non-adopter households ranged from VND 55.6 to 57.5 million, varying across the matching methods. The mean income differences between the two groups are VND 11.5, 13.7, and 13.5 million by the Nearest, Radius, and Kernel matching methods, respectively. The differences are statistically significant at the 0.01 level. Income of the adopter households is about 20-25% higher than that of households practicing traditional cropping patterns. If moving all households from the untreated group (non-adopters) to the treated group (adopters), the ATE, the average income effect at the population level, is higher and approximately VND 13.9–16.6 million. This suggests that it is important to promote the shift in crop production from mono-cropping patterns to ICPs.

Table 5. Estimated effect of ICP adoption on farm households' income

Matching Methods	Sample	Treated	Controls	Difference	
Nearest	ATT	69,076.73	57,553.705	11,523.02	***
				(20.02)	
	ATE			13,929.00	
Radius	ATT	69,490.75	55,703.978	13,786.77	***
				(24.75)	
	ATE			14452.80	
Kernel	ATT	68,802.69	55,582.6935	13,220.00	***
				(23.78)	
	ATE			16,573.13	

Note: Income in thousand Vietnamese Dong, *** statistically significant at 0.01 level

Numbers in parenthesis are percentage as compared to the control group.

4 Conclusion and Policy Implications

4.1 Conclusion

The typical ICPs in the sandy area of the coastal district of Hai Lang, as described in the present study, include intercropping of annual crops, annual crop rotation, and the rotation of two intercropping patterns. The adoption of these ICPs remains limited but is increasing. The results of the empirical logit model on ICP adoption show that farmers' decision to uptake ICPs is influenced by the gender of the household head, the wealth rank of the farming household, the plot area, participation in ICP training, and access to credit. It is important to note that better access to credit and participation in ICP training could increase the adoption of ICPs. It was also found in this study that the probability of adoption of ICPs is higher for plots with larger areas.

The study of income effects of ICP adoption using the PSM method shows that income effects are statistically significant and similar for the three matching methods used (the Nearest, Radius, and Kernel). ICP adoption could increase the annual income of farm households by VND 11.5–13.7 million, equivalent to 20–24% of the income of matched non-adopter households. Given the low-level of income of farmers in the district, this income increase is of crucial importance.

4.2 Policy Implications

Findings of this study confirm that credit access would increase the adoption of ICPs. It is suggested that a credit program providing loans with appropriate rates must be attached to the ICP promotion program. In addition, input supports for farmers, such as the provision of crop varieties and fertilizers, should be done to facilitate the adoption of the farm households. Those supports should be targeted at households that are in need of adopting ICPs. A collaborative effort between agricultural banks, farmer associations, and extension centers would be crucial for providing loans that facilitate the adoption of ICPs.

The role of extension (training on ICPs) in promoting ICP adoption is established in the present study; better access to extension services could enhance adoption. Therefore, it is of crucial importance to improve the extension system. More training courses for farmers on how to apply ICP practices should be provided. In addition, demonstrations of new ICPs should be set up so that the farmers can visit and learn.

Information from the farmer group discussion indicated that economic return from ICPs is the most important concern. In addition to technical training, it is necessary to enhance farmers' agribusiness knowledge, making them able to respond effectively to market signals such as the fluctuation of market prices of inputs and outputs of ICPs. Policies to encourage cooperation between farmers and agribusiness firms should be developed for agri-products from ICPs.

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