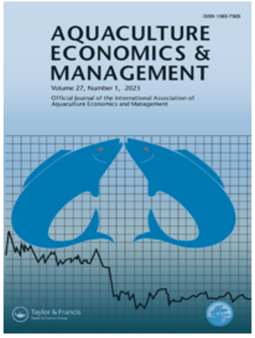

Aquaculture Economics & Management

ISSN: 1365-7305 (Print) 1551-8663 (Online) Journal homepage: www.tandfonline.com/journals/uaqm20

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AQUACULTURE ECONOMICS & MANAGEMENT
2023, VOL. 27, NO. 1, 66–95
https://doi.org/10.1080/13657305.2021.2011988

The impact of sustainable aquaculture technologies on the welfare of small-scale fish farming households in Myanmar

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ABSTRACT

This study analyzed the determinants and potential impacts of the adoption of sustainable aquaculture (SA) technologies on the welfare of small-scale aquaculture (SSA) households in Myanmar using an endogenous switching regression model. Welfare is measured by fish productivity and fish income per cycle and Household Dietary Diversity Score. Our analysis revealed that distance to the sale-point, membership in farmers' organizations, awareness of pond maintenance benefits, access to information through private extension services, and location were the main drivers behind adopting SA technologies. Results showed that adopting SA technologies increases welfare outcomes of SSA households; however, the non-adopters stand to benefit the most in terms of an increase in welfare outcomes if they adopt the technologies. Our research findings suggested that policies targeted at raising SSA households' income and dietary diversity can be realized through interventions to raise farmer's awareness, adoption, and technical know-how about the SA technologies.

KEYWORDS

Endogenous switching regression; Myanmar; small-scale aquaculture; sustainable aquaculture technologies; welfare outcomes

Introduction

The development of small-scale aquaculture (SSA) has made a significant contribution to food and nutrition security and poverty alleviation in developing countries through direct and indirect pathways (Dey et al., 2010; Little et al., 2016; Otsuka et al., 2016; Pant et al., 2014; Toufique & Belton, 2014). Studies from major fish producing countries show that a key benefit of SSA is its ability to provide a buffer for the households in the low income and

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food-deficit periods, and also to reduce seasonal cash shortages (Béné, 2009; Belton et al., 2012; Karim et al., 2017, 2020). Likewise the role of livestock within smallholder systems, the role of SSA ponds may be considered as a more easily liquefiable asset, which can be sold to acquire income (Helgeson et al., 2013; Little & Edwards, 2003). Small-scale producers with productive ponds can produce fish surplus to the subsistence requirements that can be marketed to the benefit of the broader community (Islam et al., 2004; Little & Bunting, 2005). In addition, the SSA can generate much higher income and economic spillovers than large-scale aquaculture in the rural economy through diverse pathways of production, consumption and employment engagement (Belton et al., 2012, 2018; Karim, 2006).

Despite its important role, the growth of SSA in developing countries has been constrained by several factors including contradictory land-use policy, lack of access to credit and appropriate technologies, escalating input prices, impacts of climate change and inadequate extension services (Belton et al., 2017; Duijn et al., 2018; Elfitasari & Albert, 2017; Richardson & Savedi, 2018). Moreover, although stand-alone aquaculture farms are successful for large-scale aquaculture in both developing and developed countries, individual customary aquaculture farms or production technologies that rely on traditional practices are risky ventures and no longer an option for SSA households (Prein, 2002). Therefore, renewing or modifying resources and assets used to produce goods and services, as well as adopting innovative technologies is critical for increasing productivity, economic efficiency and sustainability of SSA (Asche, 2008; FAO, 2018).

In Myanmar, aquaculture production has been growing at a rate of 9% since 2004 (Karim et al., 2020). Aquaculture has contributed to improving food security and nutrition and meeting growing fish demand in the country (Aung et al., 2021; Belton et al., 2015; Karim et al., 2020). The development of the commercial aquaculture sector in Myanmar is presently characterized by the dominance of large-scale operations and the expansion of SSA has been limited due to a number of factors including restrictive land use policies and poor infrastructure (Belton et al., 2015). However, profitability and employment opportunities generated by SSA have enticed farmers to enter the sector (Aung et al., 2021). Entry cost of SSA is low because farmers can modify their rice fields and unused backyard lands for SSA operations (Karim et al., 2020). These factors have resulted in much higher growth rates in the number and areas of SSA in Myanmar than recorded by government statistics (Belton et al., 2015).

Although SSA is not recognized in the Farmland Law 2012 as a form of agriculture (Obendorf, 2012), small-scale farmers can obtain a pond license issued by Department of Fisheries as a legal requirement for fish cultivation (Lay & Thaw, 2019). Furthermore, the assent of a village leader is also sufficient to convert a small area of agricultural into SSA ponds (Belton et al., 2015). SSA interventions for improving income and food and nutrition security among the resource poor farmers in Myanmar have been promoted by development projects in collaboration with Department of Fisheries and other international or local organizations. The evidence generated by development projects highlights the relative importance of SSA in terms of improving food, nutrition, income and welfare of rural households in Myanmar (Karim et al., 2020; Shein et al., 2014).

Despite aquaculture sector has been growing rapidly in Myanmar in recent years, growth of SSA in Myanmar have faced many challenges, including contradictory land use policies, unplanned development of SSA in response to market incentives, higher costs of production inputs, lack of efficient and adequate extension services, lack of access to financial support and improved aquaculture technologies (Aung et al., 2021). Recent studies have demonstrated that investments in improved and innovative production systems and diversified aquaculture products provide substantial benefits to producers and consumers (Kumar et al., 2018; Kumar & Engle, 2016). Findings from previous studies suggested that Integrated Aquaculture and Agriculture (IAA) could be used as a model for developing a SSA farming system (Edwards, 1998; Phong et al., 2010; Pretty, 2008). In addition, Pucher et al. (2013) also proposed a field trial of modified pond management practices (MPMPs) as a sustainable aquaculture system for SSA farmers that provide higher fish yields and net economic return for SSA farmers. However, insights into what types of aquaculture production technologies are suitable for SSA farmers in Myanmar are still lacking. Furthermore, previous studies on IAA have focused on the overview and performance of the IAA system (Ahmed et al., 2014; Huong et al., 2018) and did not move beyond analyzing the determinants of adoption and its impacts on farm productivity and income (Dey et al., 2010).

This study aimed to examine the determinants and potential impacts of SA technologies on welfare outcomes of the SSA households, which are measured by fish productivity and income per cycle, and Household Dietary Diversity Score (HDDS). The empirical evidence of this study will contribute to the limited literature on sustainable aquaculture practices, specifically about the role of IAA and MPMPs for SSA farmers, by providing micro-level information on adoption and its impacts on welfare. The empirical evidence of SSA's benefits and impacts could also contribute to regulatory reforms to allow small holders to diversify agriculture livelihoods into aquaculture production.

Overview of sustainable aquaculture technologies for small-scale aquaculture (SSA) households

Although technologies related to aquaculture have been defined more broadly in previous studies (Joffre et al., 2017; Kumar & Engle, 2016;

Little & Bunting, 2016), this study focused on the IAA and MPMPs for SSA households. There are two main types of IAA farming system depending on the biophysical conditions: (i) pond-based IAA and (ii) rice-fish farming systems. Fish is the main production activity with the integration of crops and/or livestock farming in the pond-based IAA, while rice is the main crop in the rice-fish farming system (Ahmed et al., 2014). In this study, the integration of fish farming with rice, vegetables, fruits and livestock farming is considered as the IAA system. Integrated farming systems involving aquaculture can be defined as concurrent linkages between two or more human activity systems (one or more of which is aquaculture), where these sequential linkages may have a direct impact on site or an indirect impact off-site, providing opportunities and satisfying needs for the practitioners (Prein, 2002). In addition to being able to increase fish productivity per unit of land, agro-industrial input use and risks are reduced as a result of diversification, reusing water, and recycling nutrients, and therefore the supply of a more balanced diet for farming households can be sustained (Ahmed et al., 2014; Edwards et al., 1998; Prein, 2002). The main objectives of integration between and within farms are increased intensification, diversification, productivity, sustainability, and improved natural resource use efficiency (Prein, 2002). Therefore, farm product diversification through aquaculture is considered as a promising intervention, contributing significantly to the livelihood development of poor farm households in developing countries (Dey et al., 2010; Huong et al., 2018).

Regarding MPMPs, traditionally managed pond water systems[1] result in ponds with a high loss of nutrients, increased turbidity, and reduced production of natural food resources in ponds, such as plankton, due to the removal of water from the upper pond layer. This leads to lower yields (Pucher et al., 2015; Steinbronn, 2009). Moreover, as farmers utilize pesticides in their rice fields, it harms fish and natural food in ponds and makes fish consumption risky for human health (Lamers et al., 2011). Kabir (2009) reported that lowering dietary protein to energy ratio in the feed could be compensated by enhancing natural food productivity in the pond because of a higher carbon to nitrogen input into the system that led to increase fish productivity due to an indirect effect of the diet.

A modified pond water management system[2] can enhance the production of small-scale ponds by helping decrease the turbidity of pond water and loss of nutrients caused by flushing out (Little & Bunting, 2016; Pucher et al., 2013). Pond fertilization is a relatively low cost technique that can significantly improve production efficiency because it stimulates plankton blooms to provide an essential source of natural food for fish (Belton et al., 2017). In addition, lime is also recommended in the pond preparation and repairing stage to allow optimal organic matter

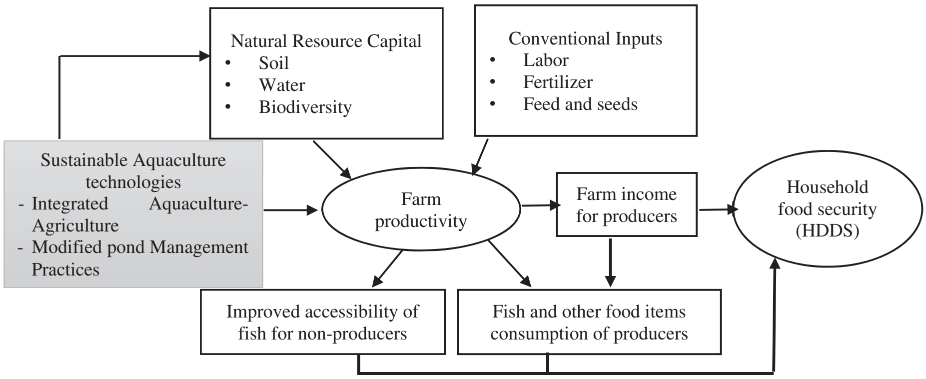

Figure 1. Schematic diagram of the impact of SA technologies on the SSA household 's welfare outcomes adapted from (Dey et al., 2010).

decomposition, disinfection of the bottom of the pond from harmful bacteria, and reduction in turbidity, all of which help ensure sustainable fish production. Compared with low-quality feed ingredients, pellet feeds enable the most effective feed uptake by fish due to the flow of required nutrients and fewer nutrients leaching into the pond, minimizing adverse environmental impacts (Pucher et al., 2013). Pucher et al. (2013) and Steinbronn (2009) stated that compared with common carp species, grass carp is very sensitive and susceptible to diseases that lead to high fish mortality. Modified pond management systems can lead to higher productivity levels, owing to the reductions in both turbidity and nutrient loss and higher levels of oxygen production during the day.

The link between the SA technologies and welfare outcomes of SSA households is presented in Figure 1. As mentioned above, SA technologies may directly affect fish productivity and improve the conservation and use of natural resources through integrated resource management. These technologies also provide remarkable benefits to small-scale rural farmers, resulting in increased home consumption of fish and higher incomes through increased farm productivity for producers and improved accessibility of fish for non-producer households. The increased income from households who adopted SA technologies will flow to the purchase of other food items, leading to improved household dietary diversity (Brummett & Noble, 1995; Dey et al., 2010). Therefore, a farm household's decision to adopt a SA technology for increased farm productivity will enhance the availability and utilization of fish and other foods at the household level.

Study area and data

The data used in this study were from an aquaculture performance assessment survey of 440 SSA households in Myanmar conducted by the project

"Scaling systems and partnerships for accelerating the adoption of improved tilapia strains by small-scale fish farmers (SPAITS)"[3] in 2019. In this survey, a combination of stratified purposive and random sampling techniques was used. The Ayeyarwady Delta Region was selected as the study area because it is the main fish-producing region in Myanmar. Specifically, a project entitled "Promoting the sustainable growth of aquaculture in Myanmar (MYFC)," had previously carried out activities to support households to engage in SSA in the five townships (Bogale, Mawlamyinegyun, Pyapon, Kyaik Latt and Daydaye) of this region. During the SPAITS project survey period, the MYFC project had five batches of SSA farmers. However, the farmers in the fifth batch were new to SSA and did not have a complete fish farming cycle at that time. Therefore, farmers in the fifth batch were excluded. A total of 1,776 fish farming households in batches one through four of the MYFC project formed the sampling frame. Each township involved in the project becomes a stratum and in consultation with field facilitators of the project and farmers, there would likely be equal opportunity for all project farmers in these project townships. Among these townships, three townships in the region, namely Daydaye, Kyaiklatt, and Phyapon, were purposely selected for the study. Then, a random sampling technique was employed to select 440 fish farming households across three townships in the project. Among the total sampled households, 17 households had no harvest in the previous fish farming cycle and were dropped, leaving 423 households for analysis. Questions were included to investigate whether farmers have adopted the SA technologies. Firstly, we created the dummy variable "MPMPs adoption" equal to one if a farm household among those selected households undertakes both practices (pond water management and chemical fertilization) and takes the value of zero otherwise. Among the aforementioned set of MPMPs, we focused on pond water management activity and chemical fertilization in this study because almost all selected households applied lime at pond preparation (100%), used pellet feed (80%), and reared non-grass carp fish species (100%). Only 54% of surveyed households practiced pond water management and 73% practiced chemical fertilization. Although most farmers applied organic or chemical fertilizer in the pond, in general the amount of natural food production in the pond is low. This can be attributed to improper pond water management, such as high water flow rates, as there is evidence of an inverse relationship between the abundance of natural food in ponds and water flow rates (Pucher et al., 2013). After generating a variable for the MPMPs adoption, a farm household among those selected households who practiced one or both SA technologies (IAA and/or MPMPs) is defined as an adopter, while a non-adopter is one who did not adopt any of these technologies.

Analytical framework and methodology

Most impact evaluation studies have used alternative statistical approaches for dealing with selection bias, including difference-in-difference (DID) and propensity score matching (PSM). The DID approach requires data collected from both the control and treatment groups before and after technology adoption (Vigani & Kathage, 2019). As our data are cross-sectional and collected after farmers have adopted the technologies, the PSM technique is the more suitable option. However, PSM can only address selection bias caused by observable factors (Abdulai, 2016; Jaleta et al., 2016). Therefore, we used the full information maximum likelihood endogenous switching regression (FIML ESR) developed by Lokshin and Sajaia (2004) to control for both selection bias and endogeneity. We then used PSM to check the robustness of the results.

Econometric framework of endogenous switching regression

Modeling impact of sustainable aquaculture (SA) technologies on welfare

Following Shiferaw et al. (2014), Ali and Abdulai (2010) and Asfaw et al. (2012), in the first stage of FIML ESR, the selection equation for the adoption of SA technologies is a dichotomous choice measurement function. The observed welfare outcomes (fish productivity, fish income and HDDS) of the adoption of SA technologies can be modeled following a random utility framework. Considering a utility maximizing ith household that faces a decision on whether or not to adopt SA technologies, the probability that the small-scale fish farming household will adopt the technologies is determined by a comparison of the expected benefit of adoption U_1 against the expected benefit of non-adoption U_0. It will adopt SA technologies only if $Y_1^* = U_1 - U_0 > 0$. The net benefit Y_1^* is an unobserved or latent response variable for the adoption of SA technologies, which is determined by observed variables Z_i and the error term ε_i:

$$\begin{aligned}\text{Adoption dummy (Adoption} = 1) = {} & \alpha_0 + \alpha_1\ (\text{AGE\_HHH}) + \alpha_2\ (\text{EDU\_HHM}) + \alpha_3\ (\text{GEN\_HHH}), + \alpha_4\ (\text{EXP}) \\ & + \alpha_5\ (\text{HHS}) + \alpha_6(\ \text{DEP\_RATIO}) + \alpha_7\ (\text{P\_SIZE}) + \alpha_8\ (\text{ASSET\_IND}) + \\ & \alpha_9\ (\text{OFF-FARM\_IN\_ DUM}) + \alpha_{10}\ (\text{LOC\_DUM }) + \alpha_{11} \\ & (\text{CLI\_SHOCK\_DUM}) + \alpha_{12}\ (\text{POND\_DIS}) + \alpha_{13}\ (\text{DIS\_SALE}) + \alpha_{14} \\ & (\text{INFO\_ NGOS\_DUM}) + \alpha_{15}\ (\text{INFO\_PRIVA TE\_DUM}) + \alpha_{16} \\ & (\text{INFO\_CLIM\_DUM}) + \alpha_{17}\ (\text{AWAR\_PON MAIN}) + \alpha_{18}\ (\text{MEMBER} \\ & \text{SHIP\_DUM}). + \text{ERROR TERM}\ (\varepsilon_i)\end{aligned} \tag{1}$$

The explanatory variables are the age of household head (AGE_HHH), education level of household members (EDU_HHM), gender of household head (GEN__HHH), experience (EXP), household size (HHS), dependency ratio (DEP_RATIO), pond size (P_SIZE), asset index (ASSET_IND), off-farm income dummy (OFF-FARM_IN_DUM), location dummy (LOC_DUM), climate shocks dummy (CLI_SHOCK_DUM), pond distance from the homestead (POND_DIS), distance to the point of sale (DIS_SALE), access to information from NGOs dummy (INFO_NGOS_DUM), access to information from private extension agent dummy (INFO_PRIVATE_DUM), access to climate information dummy (INFO_CLIM_DUM), awareness of pond maintenance benefits (AWAR_PONMAIN), membership in farmers' organizations (MEMBERSHIP_DUM), α_{1-18} are vectors of parameters to be estimated.

Applying the FIML ESR model to the welfare outcome variables, small-scale aquaculture households face two possible regimes: (1) to adopt and (2) not to adopt:

Regime 1:	outcome variables (fish productivity per cycle, fish income per cycle and HDDS)	$= \beta_0 + \beta_1$ (AGE_HHH) $+ \beta_2$ (EDU_HHM) $+ \beta_3$ (GEN_HHH) $+ \beta_4$ (EXP) $+ \beta_5$ (HHS) $+ \beta_6$ (DEP_ RATIO) $+ \beta_7$ (P_SIZE) $+ \beta_8$ (ASSET_IND) $+ \beta_9$ (OFF-FARM_IN_DUM) $+ \beta_{10}$ (LOC_DUM) $+ \beta_{11}$ (CLI_SHOCK_DUM) $+ \beta_{12}$ (POND_DIS) $+ \beta_{13}$ (DIS_SALE) $+ \beta_{14}$ (INFO_NGOS_DUM) $+ \beta_{15}$ (INFO_PRIVATE_DUM) $+ \beta_{16}$ (INFO_ CLIM_DUM) $+ \beta_{17}$ (AWAR_PONMAIN) $+$ ERROR TERM (μ_{1i})	Adoption dummy = 1 (for adopters) (2a)
Regime 2:	Outcome variables (fish productivity per cycle, fish income per cycle and HDDS)	$= \beta_0 + \beta_1$ (AGE_HHH) $+ \beta_2$ (EDU_HHM) $+ \beta_3$ (GEN_ HHH) $+ \beta_4$ (EXP) $+ \beta_5$ (HHS) $+\beta_6$ (DEP_RATIO) $+ \beta_7$ (P_SIZE) $+ \beta_8$ (ASSET_IND) $+\beta_9$ (OFF-FARM_IN_DUM) $+ \beta_{10}$ (LOC_ DUM) $+ \beta_{11}$ (CLI_SHOCK_DUM) $+ \beta_{12}$ (POND_ DIS) $+ \beta_{13}$ (DIS_SALE) $+ \beta_{14}$ (INFO_NGOS_ DUM) $+ \beta_{15}$ (INFO_PRIVATE_DUM) $+ \beta_{16}$ (INFO_CLIM_DUM) $+ \beta_{17}$ (AWAR_PON MAIN) $+$ ERROR TERM(μ_{2i})	Adoption dummy = 0 (for non-adopters) (2b)

The explanatory variables in Equations (2a) and (2b) are as mentioned above, β_{1-17} is the list of parameters to be estimated. Following Fuglie and Bosch (1995), the error terms from the above three equations are assumed to have a trivariate normal distribution with zero mean vector and the following variance-covariance matrix:

$$\sum cov(\varepsilon_i, \mu_{1i}, \mu_{2i}) = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_{\mu 1\varepsilon} & \sigma_{\mu 2\varepsilon} \\ \sigma_{\mu 1\varepsilon} & \sigma_{\mu 1}^2 & \sigma_{\mu 1\mu 2} \\ \sigma_{\mu 2\varepsilon} & \sigma_{\mu 1\mu 2} & \sigma_{\mu 2}^2 \end{bmatrix}, \tag{3}$$

where σ_ε^2 is the variance of the error term in Equation (1), $\sigma_{\mu 1}^2$ and $\sigma_{\mu 2}^2$ are the variances of error terms in Equations (2a) and (2b), respectively, and $\sigma_{\mu 1\varepsilon}$ and $\sigma_{\mu 2\varepsilon}$ are the covariance of the error terms ε_i, μ_{1i}, and μ_{2i}. The variance of the error term σ_ε^2 in Equation (1) can be assumed to be equal to one since the coefficients are only estimable up to a scale factor. Maddala (1991) states that the covariance between μ_{1i} and μ_{2i} (denoted as $\sigma_{\mu 1 \mu 2}$) is unobservable since a smallholder household cannot simultaneously be an adopter and a non-adopter. Therefore, $\sigma_{\mu 1 \mu 2}$ cannot be estimated. According to Di Falco et al. (2011), as the error term ε_i from Equation (1) is correlated with the error terms of the outcome functions μ_{1i} in Equation (2a) and μ_{2i} in Equation (2b), the conditional expected values of the error terms $\{\mu_{1i}|Y_i = 1\}$ and $\{\mu_{2i}|Y_i = 0\}$ on sample selection are non-zero and given by:

$$E\{\mu_{1i}|Y_i = 1\} = \sigma_{\mu 1\varepsilon}\left(\frac{\phi(Z_i\alpha_j)}{\Phi(Z_i\alpha_j)}\right) = \sigma_{\mu 1\varepsilon}\lambda_{1i} \tag{4a}$$

$$E\{\mu_{2i}|Y_i = 0\} = -\sigma_{\mu 2\varepsilon}\left(\frac{\phi(Z_i\alpha_j)}{1-\Phi(Z_i\alpha_j)}\right) = \sigma_{\mu 2\varepsilon}\lambda_{2i} \tag{4b}$$

where Y_i is a binary indicator that equals one for adopters and zero for non-adopters, Z_i represents explanatory variables as mentioned in Equation (1), α_j is a vector of parameters to be estimated, $\phi(.)$ is the standard normal probability density function, $\Phi(.)$ is the standard normal cumulative density function, $\lambda_{1i} = \left(\frac{\phi(Z_i\alpha_j)}{\Phi(Z_i\alpha_j)}\right)$, and $\lambda_{2i} = \left(\frac{-\phi(Z_i\alpha_j)}{1-\Phi(Z_i\alpha_j)}\right)$. Following Maddala (1991), a probit model in Equation (1) is applied to generate λ_{1i} and λ_{2i}. In the second stage of Equation (2a) and Equation (2b), the impacts of SA technologies are estimated using OLS by including the terms λ_{1i} and λ_{2i} as additional regressors to correct for selection bias.

If the covariance terms $\sigma_{\mu 1\varepsilon}$ and $\sigma_{\mu 2\varepsilon}$ are non-zero, the adoption decision and outcome equations are correlated. This indicates that the decision to adopt is an endogenous variable. The FIML ESR[4] model analyzes the selection and outcome equations simultaneously to produce consistent standard errors. The logarithmic likelihood function for the FIML ESR model, given the trivariate normal distribution of the error terms, is specified as follows:

$$\begin{aligned} lnL_i = \sum_{i=1}^{N} Y_i\left[ln\phi\left(\frac{\mu_{1i}}{\sigma_1}\right) - ln\sigma_1 + ln\Phi(\theta_{1i})\right] \\ + (1 - Y_i)\left[ln\phi\left(\frac{\mu_{2i}}{\sigma_2}\right) - ln\sigma_2 + ln(1 - \Phi(\theta_{2i})\right] \end{aligned} \tag{5}$$

where $Y_i, \phi,$ and Φ are as defined earlier *and* $\theta_{ji} = \frac{\left(Z_i\alpha_j + \rho_i\mu_{ji}/\sigma_j\right)}{\sqrt{1-\rho_j^2}}$, $j = 1, 2$, with ρ_j representing the correlation coefficient between ε_i and μ_{ji}.

According to Di Falco et al. (2011) and Maddala (1983), it is important to impose an exclusion restriction on the outcome equations. Therefore, instrumental variables that identify the selection into the treatment group are needed. It means that the explanatory variables in Equation (1) should consist of at least one variable that is not part of the explanatory variables in the outcome Equations (2a) and (2b). In this study, we use membership in farmers' organizations as the instrument like other impact assessment studies (e.g., Abdulai & Huffman, 2014; Kabunga et al., 2012; Khonje et al., 2018; Rao & Qaim, 2011) after testing its validity. Following Di Falco et al. (2011), we checked for the validity of the instrumental variable using the falsification test. If an instrument is valid, it will influence the decision to adopt SA technologies, but it will not have a direct effect on the welfare outcomes of the farm households that did not adopt SA technologies.

Estimation of counterfactuals and average treatment effects

The FIML ESR model can be applied to make the comparison of expected welfare outcomes of households who actually adopted SA technologies with respect to those who did not. Additionally, it allows us to investigate SA technologies' expected effect on the outcome variables in the counterfactual situation in which the actual adopters did not adopt and the actual non-adopters adopted. Following Lokshin and Sajaia (2004), the conditional expected treatment effects for the welfare outcomes in the four conditions were calculated as follows:

Adopters (observed in the sample)

$$E(Q_{1i}|Y_i = 1) = X_{1i}\beta_1 + \sigma_{\mu 1\varepsilon}\lambda_{1i} \tag{6a}$$

Non-adopters (observed in the sample)

$$E(Q_{2i}|Y_i = 0) = X_{2i}\beta_2 + \sigma_{\mu 2\varepsilon}\lambda_{2i} \tag{6b}$$

Adopters have decided not to adopt (counterfactual condition)

$$E(Q_{2i}|Y_i = 1) = X_{1i}\beta_2 + \sigma_{\mu 2\varepsilon}\lambda_{1i} \tag{6c}$$

Non-adopters have decided to adopt (counterfactual condition)

$$E(Q_{1i}|Y_i = 0) = X_{2i}\beta_1 + \sigma_{\mu 1\varepsilon}\lambda_{2i} \tag{6d}$$

Y_i is a binary indicator that equals one for adopters and zero for non-adopters, Q_{1i} = fish productivity per cycle, fish income per cycle and HDDS of adopters, Q_{2i} = fish productivity per cycle, fish income per cycle and HDDS of non-adopters, X_i represents vectors of explanatory variables as mentioned in Equations (2a) and (2b).

The average effect of treatment on the treated (i.e., the adopters) (ATT) is the difference between Equations (6a) and (6c), controlling for both observable and unobservable characteristics. The ATT is given by:

$$\begin{aligned} ATT &= E(Q_{1i}|Y_i = 1) - E(Q_{2i}|Y_i = 1) \\ &= X_{1i}(\beta_1 - \beta_2) + (\sigma_{\mu 1\varepsilon} - \sigma_{\mu 2\varepsilon})\lambda_{1i} \end{aligned} \tag{7}$$

Equation (7) measures the expected difference in adopters' welfare outcomes with their counterfactual if their characteristics had the same effects on the outcomes. The selection term (λ) adjusts the ATT to account for the potential effects of unobservable factors.

Similarly, this model also allows the calculation of the average effect of treatment on the untreated (i.e., non-adopters) (ATU) as the difference between Equations (6d) and (6b). The ATU is given by:

$$\begin{aligned} ATU &= E(Q_{1i}|Y_i = 0) - E(Q_{2i}|Y_i = 0) \\ &= X_{2i}(\beta_1 - \beta_2) + (\sigma_{\mu 1\varepsilon} - \sigma_{\mu 2\varepsilon})\lambda_{2i} \end{aligned} \tag{8}$$

Equation (8) measures the expected difference in non-adopters' welfare outcomes with their counterfactual if their characteristics had the same effects on the outcomes. The term (λ) captures all potential effects of unobservable factors for ATU (Shiferaw et al., 2014).

The ESR model only works if there is a valid instrumental variable. As the results from the FIML ESR model could be sensitive to the instrumental variable choice, we ran the analysis using PSM as well to check for the robustness of the results from the FIML ESR model. We followed the guidelines and steps proposed by Caliendo and Kopeinig (2008) for implementing PSM. First, we estimated the propensity score with a probit model. Second, we matched the adopters and non-adopters using two commonly applied methods: nearest neighbor matching and radius matching, which utilizes all neighbors within a given caliper to construct the counterfactual (Dehejia & Wahba, 2002). For the radius matching method, Cochran and Rubin (1973) suggested that the caliper size should be the standard deviation of the propensity score. In more recent studies, Austin (2009) suggested to use one-fifth of the standard deviation (caliper = 0.2 * sd). Austin (2011), Ko et al. (2009) and Wang et al. (2013) highlighted that using the caliper size of 0.2 of the standard deviation of the propensity score tend to have superior performance for estimating treatment effects. In this study, we followed this recommendation. Third, we tested the common support by comparing the groups' minimum and maximum propensity scores. Fourth, we calculated the treatment effects and their standard errors through the bootstrapping method with 250 replications. Finally, we addressed the sensitivity of the model.

Measurement of household dietary diversity score

In this study, Household Dietary Diversity Score (HDDS) developed by the World Food Program (FAO & WFP, 2012; WFP, 2008) was used. Following Ruel (2003), we used a seven-day recall period for the HDDS measurement from 12 food groups as it has the longest recall period with the least recall error. HDDS reflects a household's food accessibility and counts the variety of food groups consumed by a household. Although dietary diversity indicators do not comprehensively capture the food security of the households (Cafiero et al., 2014), it has been used to measure food accessibility at the household level in multi-country analysis (Hoddinott & Yohannes, 2002).

Empirical results and discussion

Descriptive statistics of adopter and non-adopter sample farmers

As a proxy for wealth, Principal Component Analysis (PCA) was used to generate an asset index, which captures information on ownership of durable household assets. Table 1 presents mean differences between the adopters and non-adopters for the variables included in the analysis. There were statistically significant differences between the adopters and non-adopters in all outcome variables. Among the explanatory variables, the household head's age, access to off-farm income, living in Phyapon Township, distance to the point-of-sale where harvested products are sold, access to information through private extension agent, awareness of pond maintenance benefits, and membership in farmers' organization were statistically significant difference between the two household groups, while the other variables were not significantly different.

The descriptive summary showed that adopters have higher fish productivity, income and HDDS scores, received less off-farm income, have more knowledge about the pond maintenance benefits and received more information on SA technologies from private extension agent and being a membership in farmers' organization compared to non-adopters. The result depicted that the adopter categories are distinguishable in terms of their greater knowledge of the existing sustainable aquaculture technologies and positive perception about these technologies. This also suggested that household's location near WorldFish regional office and other local, international organizations, and cooperatives offices that provide support to SSA farmers and market access to sell their product might be correlated

Table 1. Descriptive statistics of outcomes and explanatory variables.

Variables	Full sample ($N = 423$) Mean	Std. dev.	Adopters ($N = 314$) Mean	Std. dev.	Non-adopters ($N = 109$) Mean	Std. dev.	Mean difference
Welfare outcome:							
Fish productivity (kg/cycle)	131.79	171.72	148.24	187.21	84.40	102.96	***
Fish income (USD/cycle)	184.37	250.89	207.23	274.20	118.50	148.92	***
Household dietary diversity score (HDDS)	10.45	0.97	10.52	0.96	10.24	1.01	**
Household characteristics:							
Age of household head (years)	52	12	54	13	51	11	**
Gender of household head (1 = male)	0.93	0.25	0.94	0.24	0.91	0.29	
Education level of household members (years)	7	1.86	7	1.92	6	1.67	
Household size	5	1.75	5	1.72	5	1.83	
Fish farming experience of household head (years)	2.65	2.24	2.62	2.32	2.75	1.99	
Dependency ratio (%)	28.12	22.21	27.15	21.52	30.92	23.97	
Household wealth and farm characteristics:							
Asset index	0.00	1	0.01	1.00	−0.03	0.99	
Access to off-farm income (1 = yes)	0.20	0.39	0.17	0.37	0.29	0.45	***
Pond size (ha)	0.04	0.06	0.05	0.06	0.04	0.07	
Phyapon region (1 = yes)	0.70	0.45	0.75	0.44	0.58	0.49	***
Pond distance from homestead (walking minutes)	3.22	5.29	3.05	5.14	3.71	5.72	
Distance to point-of-sale (miles)	1.36	4.51	1.53	5.15	0.87	1.55	**
Climate shock(s) in last production cycle (1 = yes)	0.57	0.49	0.55	0.49	0.62	0.48	
Information sources:							
Access to information through NGOs (1 = yes)	0.86	0.35	0.85	0.36	0.88	0.31	
Access to information through private extension agent (1 = yes)	0.12	0.33	0.15	0.35	0.06	0.23	***
Access to climate information (1 = yes)	0.56	0.50	0.57	0.49	0.51	0.50	
Awareness of pond maintenance benefits (1 = yes)	0.75	0.43	0.80	0.40	0.62	0.49	***
Membership in farmers' organizations (1 = yes)	0.85	0.35	0.90	0.30	0.74	0.44	***
Costs and return of production per cycle:							
Total variable cost for fish production (USD/cycle)	104.45	88.89	115.43	94.67	72.79	59.51	***
Gross revenue (USD/cycle)	184.37	250.89	207.23	274.20	118.50	148.92	***
Gross margin (USD/cycle)	79.92	211.26	91.79	234.38	45.70	116.61	***
Average daily wage for family labor (USD)	2.58	25.72	3.09	29.70	1.09	5.08	

Notes: $^{***}p < 0.01$ and $^{**}p < 0.05$. At the market exchange rate (retrieved from https://www.exchange-rates.org), 1 USD in October 2020 is equivalent to 1,300 Myanmar Kyat.
Source: Authors' calculation.

with decision to adopt. In this study, although adopters earned a higher average gross margin per cycle, their variable cost of fish production per cycle was also higher than that of non-adopters. These differences were statistically significant. Since SA technologies incur additional costs, farmers will adopt only if the increase in total expected revenue outweighs that in total expected costs. These findings confirmed that SA technologies may enhance product yield, but capital and labor requirement constraints may prohibit the adoption of SA technologies by small-scale farming households.

Endogenous switching regression estimation results

This section reports the factors that influence a household's decision to adopt SA technologies, as well as its impacts on the outcome variables using the FIML ESR model. This model jointly estimates the selection and outcome equations in all specifications. Following the Di Falco et al. (2011) procedure on the simple rejection test, membership in farmers' organizations was considered a valid instrumental variable because it was a statistically significant driver in the decision to adopt SA technologies (p-value $=$ 0.0196) but did not significantly influence the welfare outcome variables of the households that did not adopt the technologies with p-values of 0.2900 in fish productivity per cycle, 0.2154 in fish income per cycle, and 0.1041 in HDDS.

Determinants of SA technologies' adoption

The coefficients of the ESR model estimates presented in the second columns of Tables 2–4 are the determinants of adoption estimates. There were differences in some coefficient estimates of the selection equations, but the estimates' sign and significance were similar, indicating robustness of the overall research findings.

Regarding the determinants of the adoption of SA technologies, age of household head had a negative effect on the adoption of SA technologies across all specifications. Having off-farm income negatively affected the decision to adopt SA technologies. The regional differences, as indicated by the statistically significant region dummy, were partly due to distance and accessibility of transportation to extension offices. We have also found the positive and significant relationship between distance to the point of sale and adoption decision. Moreover, access to information provided by private extension agents also played a significant and critical role in determining farm household's decision to adopt. Participation in the farmers' organizations was positive and statistically significant, probably because these organizations facilitate the flow of information about the SA technologies. Our results show that SA technologies were mostly adopted by the households with older household head, who have less access to off-farm income activities, more accessibility of information about the aquaculture technologies through extension services provided by local and international

Table 2. Full information maximum likelihood estimates of endogenous switching regression model for SA technology adoption and impact of adoption on fish productivity per cycle.

Explanatory variables	ESR stage I Determinants of adoption	ESR stage II Fish productivity per cycle of adopters	 Fish productivity per cycle of non-adopters
Age of household head (years)	−0.013**	0.012**	0.011
	(0.005)	(0.006)	(0.008)
Education level of household members (years)	0.011	0.018	−0.071
	(0.041)	(0.039)	(0.067)
Gender of household head (1 = male)	0.229	−0.274	−0.215
	(0.259)	(0.273)	(0.338)
Fish farming experience of household head (years)	0.003	0.024	−0.012
	(0.028)	(0.029)	(0.049)
Household size	−0.037	0.030	−0.030
	(0.038)	(0.039)	(0.054)
Dependency ratio (%)	−0.006*	0.003	0.000
	(0.003)	(0.003)	(0.005)
Pond size (hectare)	1.392	3.105**	1.431
	(1.384)	(1.220)	(1.753)
Asset index	−0.066	0.053	0.111
	(0.070)	(0.067)	(0.105)
Access to off-farm income (1 = yes)	−0.381**	0.424**	−0.092
	(0.166)	(0.178)	(0.235)
Location dummy(1 = Phyapon)	0.430***	0.157	0.153
	(0.150)	(0.156)	(0.228)
Climate shock(s) (1 = yes)	−0.121	−0.199	−0.465**
	(0.141)	(0.135)	(0.206)
Pond distance from the homestead (walking minutes)	−0.012	−0.001	−0.017
	(0.013)	(0.013)	(0.019)
Distance to the point of sale (miles)	0.069*	0.042***	0.261***
	(0.037)	(0.014)	(0.072)
Access to information from NGOs (1 = yes)	0.458	0.136	−0.247
	(0.328)	(0.348)	(0.389)
Access to information from private extension agent (1 = yes)	0.938*	−0.013	−0.679
	(0.375)	(0.360)	(0.531)
Access to climate information (1 = yes)	0.038	0.062	0.077
	(0.145)	(0.141)	(0.197)
Awareness of pond maintenance benefits (1 = yes)	0.213	0.105	0.330
	(0.162)	(0.170)	(0.213)
Membership in farmers' organizations (1 = yes)	0.509***		
	(0.161)		
Constant	0.029	3.593***	3.696***
	(0.603)	(0.620)	(0.986)
σ_1 and σ_2		1.218***	0.978
		(0.074)	(0.122)
ρ_1 and ρ_2		−0.868***	−0.417
		(0.068)	(0.306)
LR test of independent equations χ^2		12.85***	

Notes: Numbers in parentheses are standard errors. ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.
Source: Authors' calculation.

organizations and market access. Lower accessibility of inputs and information about the technologies and higher access to off-farm income activities reduce the adoption of the technologies. Regarding the percentage of household income coming from different sources, the percentage of farm income including fish, crop and livestock is the highest for the adopters while off-farm income is the main source of income for the non-adopters.

Table 3. Full information maximum likelihood estimates of endogenous switching regression model for SA technology adoption and impact of adoption on fish income per cycle.

Explanatory variables	ESR stage I Determinants of adoption	ESR stage II Fish income per cycle of adopters	ESR stage II Fish income per cycle of non-adopters
Age of household head (years)	−0.013**	0.013**	0.010
	(0.006)	(0.006)	(0.008)
Education level of household members (years)	0.007	0.020	−0.080
	(0.042)	(0.039)	(0.069)
Gender of household head (1 = male)	0.220	−0.253	−0.198
	(0.260)	(0.272)	(0.348)
Fish farming experience of household head (years)	0.005	0.018	−0.008
	(0.029)	(0.029)	(0.050)
Household size	−0.033	0.030	−0.030
	(0.038)	(0.039)	(0.056)
Dependency ratio (%)	−0.005	0.003	0.000
	(0.003)	(0.003)	(0.005)
Pond size (hectare)	1.529	3.104**	0.495
	(1.392)	(1.209)	(1.815)
Asset index	−0.057	0.066	0.125
	(0.070)	(0.067)	(0.108)
Access to off-farm income (1 = yes)	−0.404**	0.427**	−0.126
	(0.165)	(0.177)	(0.243)
Location dummy(1 = Phyapon)	0.430***	0.225	0.250
	(0.152)	(0.155)	(0.235)
Climate shock(s) (1 = yes)	−0.141	−0.219	−0.399*
	(0.142)	(0.134)	(0.213)
Pond distance from the homestead (walking minutes)	−0.014	−0.005	−0.013
	(0.013)	(0.013)	(0.019)
Distance to the point of sale (miles)	0.078**	0.034**	0.253***
	(0.038)	(0.014)	(0.075)
Access to information from NGOs (1 = yes)	0.485	0.074	−0.068
	(0.330)	(0.346)	(0.403)
Access to information from private extension agent (1 = yes)	0.967**	−0.030	−0.718
	(0.379)	(0.359)	(0.548)
Access to climate information (1 = yes)	0.033	0.056	0.100
	(0.147)	(0.140)	(0.203)
Awareness of pond maintenance benefits (1 = yes)	0.240	0.086	0.307
	(0.162)	(0.169)	(0.222)
Membership in farmers' organizations (1 = yes)	0.508***		
	(0.167)		
Constant	0.007	11.018***	11.027***
	(0.610)	(0.615)	(1.011)
σ_1 and σ_2		1.201***	1.016
		(0.072)	(0.132)
ρ_1 and ρ_2		−0.826***	−0.452
		(0.078)	(0.290)
LR test of independent equations χ^2		11.82***	

Notes: Numbers in parentheses are standard errors. ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.
Source: Authors' calculation.

Younger household heads may be more willing to adopt new technologies because they tend to be less risk averse and, thus, are more willing to bear the risk of adopting a new technology. When households have other sources of income and are less reliant on the income from farm activities, there could be less focus and financial investments on the new technologies in this sector. They may also not have time to learn about these technologies. The statistical significant regional differences may also be because

Table 4. Full information maximum likelihood estimates of endogenous switching regression model for SA technology adoption and impact of adoption on HDDS.

Explanatory variables	ESR stage I Determinants of adoption	ESR stage II HDDS of adopters	HDDS of non-adopters
Age of household head (years)	−0.012**	0.011**	0.002
	(0.006)	(0.005)	(0.008)
Education level of household members (years)	−0.006	0.034	0.114*
	(0.042)	(0.034)	(0.068)
Gender of household head (1 = male)	0.049	0.262	0.462
	(0.266)	(0.236)	(0.344)
Fish farming experience of household head (years)	0.023	−0.061**	−0.029
	(0.032)	(0.025)	(0.050)
Household size	−0.026	0.039	−0.026
	(0.039)	(0.033)	(0.055)
Dependency ratio (%)	−0.004	0.000	0.005
	(0.003)	(0.003)	(0.005)
Pond size (hectare)	1.110	−1.798*	−0.814
	(1.318)	(1.034)	(1.809)
Asset index	−0.041	0.103*	0.250**
	(0.073)	(0.058)	(0.107)
Access to off-farm income (1 = yes)	−0.423**	0.174	0.001
	(0.170)	(0.156)	(0.243)
Location dummy(1 = Phyapon)	0.417***	−0.110	0.139
	(0.156)	(0.144)	(0.234)
Climate shock(s) (1 = yes)	−0.149	0.113	0.127
	(0.146)	(0.118)	(0.214)
Pond distance from the homestead (walking minutes)	−0.011	0.007	0.002
	(0.015)	(0.011)	(0.020)
Distance to the point of sale (miles)	0.067*	0.008	0.005
	(0.036)	(0.012)	(0.073)
Access to information from NGOs (1 = yes)	0.253	0.112	−0.571
	(0.325)	(0.305)	(0.394)
Access to information from private extension agent (1 = yes)	0.668*	0.186	−0.288
	(0.382)	(0.327)	(0.527)
Access to climate information (1 = yes)	−0.025	−0.046	−0.091
	(0.152)	(0.121)	(0.198)
Awareness of pond maintenance benefits (1 = yes)	0.303*	0.020	−0.196
	(0.159)	(0.151)	(0.233)
Membership in farmers' organizations (1 = yes)	0.484**		
	(0.202)		
Constant	0.358	9.719***	9.068***
	(0.628)	(0.546)	(1.011)
σ_1 and σ_2		1.023	1.019
		(0.082)	(0.146)
ρ_1 and ρ_2		−0.752***	−0.500
		(0.164)	(0.281)
LR test of independent equations $\chi2$		2.19	

Notes: Numbers in parentheses are standard errors. ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.
Source: Authors' calculation.

Phyapon Township is closer to the WorldFish regional office and other local, international organizations, and cooperatives offices that provide support to SSA farmers. Those farmers who reside near the government and non-government organization offices have better access to information about the advantages of improved technologies and are likely to adopt and allocate more land to these technologies. The positive and significant relationship of distance to the point of sale indicated that households who have easier access to the main market when selling their products have a higher probability of adopting the SA technologies. As shown in previous studies, information provision sources play a vital role in determining the decision to adopt technology (Abdulai, 2016; Di Falco et al., 2011). Aquaculture extension is the system of learning and building the human capital of farming households by providing the information and exposing them to the production technologies, which can increase aquaculture productivity, and, in turn, fish income and dietary diversity of the households.

Impact on fish productivity, income and HDDI

The third and fourth columns of Tables 2–4 report the impacts of adoption on fish productivity per cycle, fish income per cycle and HDDS of adopters and non-adopters. Looking at the estimates from the second stage of FIML ESR model, the differences in the outcome equations coefficient between the adopters and non-adopters illustrated the presence of heterogeneity in the sampled households. Notable differences between the two household groups confirmed that the switching regression model is more appropriate compared to data pooling in one regression for all outcome variables. The value of σ_j in the lower part of Tables 2–4 is the square root of the variance of the error terms from the welfare outcome equations. The significance of σ_j also confirmed the welfare outcomes of adopters and non-adopters are heterogeneous, indicating that there are differences in the coefficients of the outcomes (fish productivity, income and HDDS) equations between adopters and non-adopters. The variables that explained this heterogeneity are presented in columns 3 and 4 of Tables 2–4.

In the log of fish productivity and income equations, while the variable representing access to off-farm activities affected fish productivity and income of adopters, the effect was insignificant among non-adopters. A possible explanation for this variable is that generating income from other income sources can offer the necessary financial resources required for fish production activities, which, in turn, enhances fish productivity. The age of the household head has significant and positive effects on fish productivity and income of adopters. It may actually explain that older farmers have more experience managing fish ponds to enhance fish productivity. While pond size has a significant and positive effect on both outcomes of adopters, it has insignificant effect for non-adopters. This suggests that economies of scale are present for adopters but not for non-adopters, which is consistent with (Lapple et al., 2013). While climate shocks have a significant and negative effect on the fish productivity and income of non-adopters, it has no significant effect for adopters. This result implies that adopting SA technologies, such as farm diversification and modified pond management practices help adopters reduce production losses from climate shocks in the previous fish production cycle. Due to flooding almost every year in the study area, access to information about climate change is very important for non-adopters to reduce the negative effect of climatic shocks on their fish production. The distance to the point of sale was positive and significantly affected both adopters and non-adopters, indicating that households who sell their output in the main market received higher price of output, which, in turn, increase fish productivity and income by investing more inputs and operation management.

Likewise, the coefficient estimates in the HDDS equation appeared to have impacts on adopters and non-adopters differently. While variables such as household head's age, experience and pond size, affected HDDS of adopters, only education level of household members affected the HDDS of non-adopters. As mentioned earlier, older farmers have more experience managing fish ponds to enhance fish productivity, which in turn increase HDDS of adopters. Non-adopters with higher education level of household members can achieve higher HDDS because higher education level of household members is likely to help non-adopters households to generate off-farm incomes that enhances their diets, which is consistent with Parvathi (2018). Asset index variable significantly and positively influenced the HDDS of both adopters and non-adopters, indicating that the assets index as a proxy of wealth plays a role in improving household dietary diversity which is in line with the study by Parvathi (2018).

The statistical significance of ρ_j showed that the error terms of Equation (1) and Equations (2a) and (2b) are correlated, implying that selection bias occurred in the adoption decision. These results also highlighted that some unobservable factors that influence a household's decision to adopt could also affect its welfare outcomes. Results from the FIML ESR model supported our assumption that the decision to adopt the SA technologies is endogenous. The negative and significant covariance terms for ρ_j point to a positive selection bias, indicating that SSA households with higher fish productivity, income, and HDDS are also more likely to adopt the SA technologies. This research finding is in line with the empirical evidence observed in the agriculture sector by Bidzakin et al. (2019), Abdulai (2016) and Abdulai and Huffman (2014).

Table 5 presents the expected household welfare outcomes from the adoption of SA technologies under actual and counterfactual conditions for SSA households. Cells (a) and (b) reports expected outcomes under actual condition, while (c) and (d) reports those under counterfactual condition. The expected fish productivity per cycle, fish income per cycle, and HDDS were 4.42, 11.93, and 10.52, respectively, for households who actually adopted the

Table 5. Average treatment effects: endogenous switching regression model.

	Decision stage			
Outcome variables	Adopters ($N = 314$)	Non-adopters ($N = 109$)	Treatment effects	Increase (%)
Fish productivity per cycle (kg)[a]				
Adopters	(a) 4.42 (0.03)	(c) 3.53 (0.08)	ATT = 0.89 (0.09)***	25.21
Non-adopters	(d) 5.99 (0.05)	(b) 3.91 (0.06)	ATU = 2.08 (0.07)***	53.19
Fish income per cycle (MMK)				
Adopters	(a) 11.93 (0.03)	(c) 10.93 (0.08)	ATT = 1.00 (0.09)***	9.15
Non-adopters	(d) 13.39 (0.05)	(b) 11.39 (0.06)	ATU = 2.00 (0.08)***	17.56
HDDS				
Adopters	(a) 10.52 (0.02)	(c) 9.48 (0.02)	ATT = 1.04 (0.03)***	10.97
Non-adopters	(d) 11.73 (0.03)	(b) 10.24 (0.04)	ATU = 1.47 (0.05)***	14.36

[a]The average fish productivity and fish income per cycle is the expected mean productivity and income of adopters and non-adopters based on the FIML ESR model estimates. As the outcome variable is the logarithm of fish productivity in kg and fish income in MMK per cycle, the expected mean values are also displayed in the logarithmic form.

Notes: Numbers in parentheses are standard errors. ***$p < 0.01$.

Source: Authors' calculation.

SA technologies, and were 3.91, 11.39, and 10.24, respectively, for the actual non-adopters. The average treatment effects of SA technologies on the adopters (ATT) indicated that the fish productivity, fish income, and HDDS of adopters were higher by 25.21%, 9.15%, and 10.97%, respectively, compared with the counterfactual situation in which they had not adopted these SA technologies. Concerning the average treatment effects of SA technologies on the non-adopters (ATU), the fish productivity, fish income, and HDDS of non-adopters would have been higher by 53.19%, 17.56%, and 14.36%, respectively, if they had adopted the SA technologies (counterfactuals). These findings confirmed that the adoption of SA technologies significantly and positively influence the welfare outcomes of SSA households. However, the impact of SA technologies is more critical for the non-adopters, because the average treatment effect was larger for the farm households that did not adopt the SA technologies (ATU) compared with those that actually adopted (ATT). This highlighted that there are some important sources of heterogeneity that make that non-adopters "better producers "than the adopters.

Propensity score matching (PSM) estimation results

For brevity, we do not present detailed estimates of the probit model. Estimates of the common support region and propensity score distribution are displayed in Figure A1. The red bars show the distribution of propensity scores for adopters, blue bars show the distribution for non-adopters, and green bars show the off-support households, which are adopters that do not have a matching pair of non-adopters (Shiferaw et al., 2014). As depicted in Figure A1, a visual inspection of the density distributions of the estimated propensity scores for the two groups indicated that the common support condition is satisfied: there was a substantial overlap in the

Table 6. Average treatment effects: Propensity score matching.

Outcome variable	Matching algorithm	Mean of outcome variables		ATT difference
		Adopters ($N = 314$)	Non-adopters ($N = 109$)	
Fish productivity per cycle	Radius	4.36	4.09	0.27 (0.16)*
	Nearest neighbor with replacement	4.43	4.05	0.38 (0.18)**
Fish income per cycle	Radius	11.87	11.59	0.27 (0.15)*
	Nearest neighbor with replacement	11.93	11.55	0.38 (0.18)**
HDDS	Radius	10.52	10.33	0.19(0.11)*
	Nearest neighbor with replacement	10.52	10.30	0.22 (0.12)*

Notes: Numbers in parentheses are the bootstrapped standard errors. **$p < 0.05$ and *$p < 0.1$.
Source: Authors' calculation.

propensity score distribution for the adopters and non-adopters. The estimated propensity scores are shown in Table A1. The adopters whose estimated propensity scores are off-support did not have a matching partner of non-adopters. Therefore, these households were not included in the calculation of the ATT parameter. Table 6 reports the estimates of the average treatment effects of SA technologies on welfare outcomes estimated by radius matching method and nearest neighbor matching (NNM). The results from PSM indicated that adopting SA technologies had a significant impact on the fish productivity, fish income and HDDS of the households. Fish productivity per cycle and income between adopters and non-adopters was statistically different at the 10% and 5% level, respectively by radius matching and nearest neighbor matching methods. Household dietary diversity scores between adopters and non-adopters was also statistically different at 10% level by both methods. Moreover, the ESR model estimates for all outcome variables were higher than PSM based estimated results. The justification is that the ESR model estimate the potential impact of technology adoption decision by controlling for both unobserved and observed factors, while PSM can only control for the observed factors.

Table A2 presents results from covariate balancing tests before and after matching. The standardized mean differences for overall covariates (around 19% before matching) were reduced to 4% and 7.2% after radius matching and nearest neighbor matching, respectively. The pseudo-R^2 also dropped significantly from 12.1% before matching to 1.1% and 3.2% after matching. The low pseudo-R^2, low mean standardized bias, and high total bias reduction after matching suggested that the proposed specification of the propensity score was successful in terms of balancing the distribution of covariates between adopters and non-adopters. Regarding sensitivity to hidden bias, the critical levels of gamma (Γ) were in the range of 1.45 to 1.65 depending on the matching method and outcome variables. These results are very close to those reported by other studies assessing the impacts of agricultural innovations (Ali & Abdulai, 2010; Becerril & Abdulai, 2010; Kassie et al., 2011).

Conclusions and policy implications

This study evaluated factors influencing farming households' decision to adopt SA technologies and the potential impact of this adoption on fish productivity per cycle, fish income per cycle, and HDDS. The FIML ESR model was applied to estimate the welfare effect of SA technologies adoption.

The analysis of the determinants of adoption highlighted that, household head's age, distance to the point-of-sale, membership in farmers' organizations, access to information through private extension agent, awareness of pond maintenance benefits, and location were the main drivers behind adopting SA technologies. Households who can easily access the main market have a higher probability of adopting the SA technologies. Therefore, enhancing market access for selling farm products and purchasing pond inputs is crucial to encourage the adoption of new technologies. Moreover, membership in farmers' organizations and private extension services may raise small-scale farmers' awareness about new technologies through information dissemination.

We can draw two main conclusions from the results of this study. First, the adopters of SA technologies in the study area had systematically different characteristics from the non-adopters. These differences represent sources of variations between the two household groups. Second, results from the FIML ESR model suggested that after taking into account all confounding factors, the adoption of SA technologies increases the welfare outcomes of SSA households. The results from this paper generally confirmed the potential direct role of SA technology adoption on improving the welfare of SSA farmers. However, while both groups of SSA farm households would benefit from the adoption of SA technologies, the non-adopters would benefit the most in terms of an increase in welfare outcomes if they are to adopt the SA technologies as ATU for outcomes is higher than ATT. In other words, when non-adopters are aware of the potential benefits from adopting SA technologies with an increased investment cost, they benefit more from this awareness with that investment. In addition, those farm households have some characteristics (e.g., unobserved skills) that would make them more increasing welfare outcomes when they adopt these technologies.

The higher benefits to non-adopters, had they adopted the technology, indicates the potential existence of other limiting factors and barriers to adoption including access to information, knowledge of aquaculture production, access to quality inputs, higher prices of inputs, access to credit, and poor water availability. Promoting farmers' awareness and knowledge about the aquaculture through information dissemination programs and input supports may be a useful and effective policy to induce small-scale farm households to adopt SA technologies, which could result in greater welfare outcomes for the SSA farmers.

Findings from this study also suggested important insights for designing effective development policies to promote adoption of SA technologies and SSA sector development, particularly land use policy. Land use reform should be promoted to give farmers the right to diversify their agricultural land uses, including small-scale aquaculture for increasing food and nutrition security, contributing to poverty reduction and rural development. In addition to land use policy, as evidence of this study informed, the government should emphasize other policy measures, such as encouraging sustainable input supply and allocating adequate funding for human resource development programs to strengthen extension services and rural organizations. In addition, road infrastructure needs to be improved for better access to markets.

Future research based on randomized experimental data and/or action-research pond trials related to various SA technologies in Myanmar should be carried out to find out more about the SA technologies that are suitable for small-scale fish farmers. More research efforts can help better understand the role of different aquaculture technologies and identify the most successful ones for SSA farmers.

Notes

1. In a traditional pond water management system, water from all surrounding sources (paddy fields, channels, and gardens) flows into fish ponds without any control system, so water either flows in constantly through holes in dikes or through openings created for that purpose (Reinhardt et al., 2012).
2. In order to reduce the impacts of pesticides or eroded particles derived from neighboring fields (particularly paddy fields), proper pipes or channels are installed around ponds to control inflows and outflows.
3. For more information on the SPAITS project, see the following website: worldfishcenter.org
4. The full information maximum likelihood method was estimated using the 'movestay' command in Stata 16.

Acknowledgments

This research is a contribution to the CGIAR Research Program on Fish Agrifood Systems (FISH).

Funding

Funding support to the study was provided by the German Federal Ministry for Economic Cooperation and Development (BMZ), on a project titled "Scaling Systems and

Partnerships for Accelerated Adoption of Improved Tilapia Strains (SPAITS)" [grant number 81219436], and the German Academic Exchange Service (DAAD). The views expressed in this document cannot be taken to reflect the official opinions of these organizations.

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APPENDICES

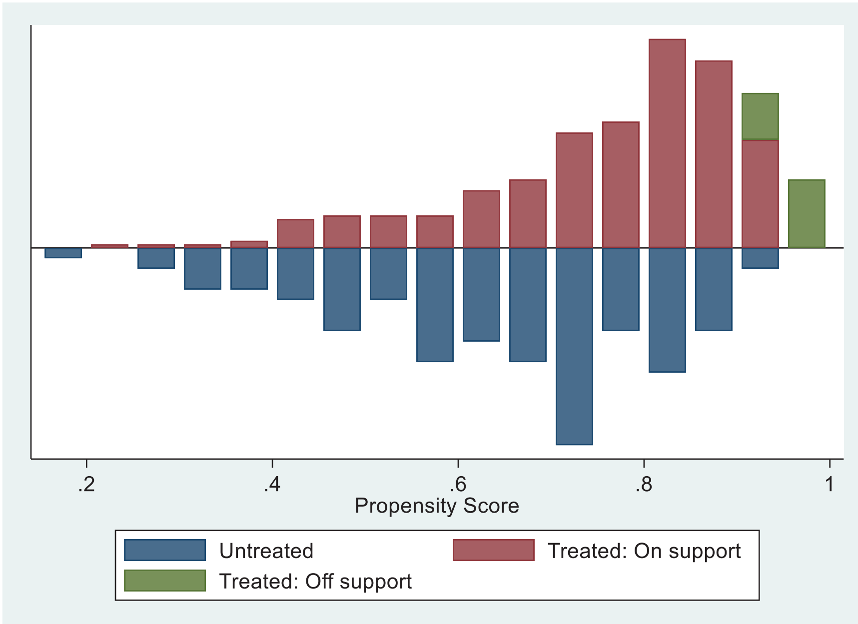

Figure A1. Distribution of propensity scores and common support area. Source: Prepared by Authors.

Table A1. Estimated propensity scores for sampled households.

Household type	No.	Mean	Std. dev.	Min	Max
Adopters	314	0.78	0.15	0.23	1.00
Non-adopters	109	0.65	0.17	0.18	0.94
All sampled households	423	0.74	0.16	0.18	1.00

Source: Authors' calculation.

Table A2. Matching quality indicators.

Matching algorithm	Pseudo R^2 before matching	Pseudo R^2 after matching	LR X^2 (*p*-value) Before matching	LR X^2 (*p*-value) After matching	Mean standardized bias before matching	Mean standardized bias after matching	Total %|bias| reduction	Critical level of hidden bias (Γ)
Radius	0.121	0.011	58.43 ($p = 0.000$)	8.65 ($p = 0.967$)	18.60	4.0	78.50	1.4–1.45
Nearest neighbor with replacement	0.121	0.032	58.43 ($p = 0.000$)	28.24 ($p = 0.058$)	18.60	7.20	61.29	1.5–1.65

Source: Authors' calculation.