Aquaculture Reports 21 (2021) 100841

Contents lists available at ScienceDirect

Aquaculture Reports

journal homepage: www.elsevier.com/locate/aqrep

Technical efficiency of small-scale aquaculture in Myanmar: Does women's participation in decision-making matter?

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A R T I C L E I N F O

Keywords:
Input use efficiency
Women's participation in decision-making
Data envelopment analysis
Small-scale aquaculture
Myanmar

A B S T R A C T

Efficient use of inputs is crucial for sustainable aquaculture productivity growth, increased profitability, and improved livelihoods in developing countries. Studies have shown that women's participation in decision-making (WPDM) can influence technical efficiency among agricultural crops farmers. However, rigorous empirical evidence in small-scale aquaculture is inadequate. Using data from 440 small-scale aquaculture households in the Ayeyarwady Delta region of Myanmar, this study: (*a*) measures technical efficiency using radial, non-radial and two-stage double bootstrap data envelopment analysis (DEA); and (*b*) examines the effect of WPDM on technical efficiency. Results reveal that most households perform 45–60% below the production frontier indicating they are not technically efficient. WPDM correlates with a significant increase in technical efficiency suggesting that women's empowerment contributes to optimal use of inputs and improved on-farm aquaculture performance. Practicing polyculture and implementing climate change adaptation strategies correlate with enhanced efficiency. Practicing polyculture with compatible fish species allows advantageous interactions and coexistence which improve inputs utilization and reduce wastes. Judicious use of inputs as a strategy for addressing climatic shocks possibly explains the positive correlation between adaptation and technical efficiency. Together, the findings highlight the important need to promote interventions targeted at improving technical efficiency of small-scale aquaculture producers. Improving technical efficiency can reduce production costs, increase net farm income, and provide a sustainable supply of nutritious foods, a source of essential micronutrients such as vitamins and omega-3 fatty acids, and affordable animal-source protein. Programs and policies aimed at increasing aquaculture productivity would benefit by including interventions to reduce gender inequality and promoting equity.

1. Introduction

Small-scale fish farming was almost non-existent in Myanmar before the country embarked on the economic reforms in 2012 (Driel and Nauta, 2014). The reforms targeted poverty reduction and rural development by introducing new agricultural policies promoting diversification of smallholder agriculture, including fish farming (NESAC, 2016). The number of small and medium-scale aquaculture producers has since then expanded rapidly (Belton et al., 2015). Entry cost of small-scale aquaculture is low because farmers can modify rice fields and utilize unused backyard lands (Karim et al., 2020). Therefore, small-scale aquaculture development is an important and promising intervention to meet the growing fish demand and improve the livelihoods of poor and vulnerable households in rural Myanmar.

Small-scale aquaculture sector faces many challenges including low adoption of improved production technologies and high costs of production inputs. Therefore, it is imperative for them to improve the technical efficiency level, in order to better utilize the limited and costly resources, which will enhance fish farming performance and farm income. In addition, optimal input use is very important for mitigating

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https://doi.org/10.1016/j.aqrep.2021.100841
Received 28 October 2020; Received in revised form 23 July 2021; Accepted 27 August 2021
Available online 4 September 2021

environmental problems and ensuring the long-term development of the aquaculture sector (Long et al., 2020a; Iliyasu and Mohamed, 2016). Reinhard et al. (1999) defined that environmental efficiency is an input-oriented, single-factor measure of technical efficiency of the environmentally detrimental input. Although technical efficiency is a necessary condition for environmental efficiency, if a high level of environmentally detrimental inputs is employed, the high degree of technical efficiency could be compatible with a relatively low degree of environmental efficiency. Therefore, the extent of divergence between the two efficiency measures depends on how much the environmentally detrimental inputs can be substituted in the production process.

Despite the potential of small-scale aquaculture for rural development in Myanmar, a relevant question for agricultural policy makers is whether and how technical efficiency of the sector can be improved to achieve either the current output level with less inputs or more output with the current input levels. Answering this question is imperative and requires solid understanding of farmers' current level of technical efficiency and its determining factors. Most of the existing literature in aquaculture sector (e.g., Hai et al., 2018; Long et al., 2020a) analyzed technical efficiency of all inputs simultaneously, assuming that all inputs used in fish production can be reduced by the same magnitude. However, some inputs are more controllable than others. Therefore, inefficient farmers have better opportunities to improve their farm operations by optimizing specific input amounts (Ngoc et al., 2018).

Women play a significant role as laborers or managers and decision-makers in aquaculture production and value chains (FAO, 2018). Women's participation in aquaculture can contribute to improving households' well-being (Weeratunge et al., 2010). Evidence shows that empowering women in agriculture generates multiple benefits. For example, empowering women can improve their status both inside and outside of the households, including participation in decision-making processes, access to and control over resources, and freedom of movement, all of which may increase technical efficiency, agricultural productivity, and food and nutrition security of the households (Seymour, 2017; Bozoğlu and Ceyhan, 2007; Zereyesus, 2017; Diiro et al., 2018; Wouterse, 2019; Adeyeye et al., 2019; Sell et al., 2018). Women's active involvement in small-scale aquaculture activities has been shown to increase households' income and food security (Aregu et al., 2017; Shirajee et al., 2010; Weeratunge et al., 2010). Furthermore, participation of women in small-scale fisheries has been shown to enhance welfare outcomes of both fishing households and employees (Liontakis et al., 2020). Sustainable improvement in the aquaculture sector's productivity and technical efficiency level depends upon the recognition of the crucial role women played in aquaculture activities (Luomba, 2013). For example, evidence in Cambodia showed that aquaculture ponds managed by women tend to generate higher yields than those managed by men. In some parts of China and Thailand, women bear the sole responsibility for aquaculture farm production because of male migration to cities (Kusakabe, 2003). Women have more knowledge in terms of management of aquaculture production activities such as cage preparation, pond maintenance, pond feeding, removal of unused feeds, procuring of good quality seed, and stocking of fish, leading to higher productivity and technical efficiency of fish farming (Ahmed et al., 2012).

Conceptually speaking, technical efficiency of small-scale aquaculture is influenced by a combination of socioeconomic characteristics of farming households, farm characteristics, and environmental factors (Alam et al., 2012; Hai et al., 2018; Cinemre et al., 2006; Iliyasu and Mohamed, 2016; Singh et al., 2009; Tan et al., 2011; Onumah et al., 2010). However, empirical evidence about the relationship between women's empowerment and technical efficiency is missing in aquaculture. Among different dimensions of women's empowerment measurement, household level decision-making, access to and control over household resources and freedom of movement are the most common proxy indicators (Malhotra et al., 2002). Recent methods for measuring women's empowerment including the Women's Empowerment in Agriculture Index (WEAI) by Alkire et al. (2013) and Women's Empowerment in Livestock Index (WELI) by Galiè et al. (2018), incorporate decision-making as a key dimension of empowerment. The consideration of women's participation in decision-making (WPDM) as a measurement of empowerment is also presented in Allendorf (2007) and Sariyev et al. (2020a, 2020b). In this study, intra-household decision--making process is used as a proxy measurement of women's empowerment.

By and large, studies using decision-making domains as measurements of women's empowerment have considered only one out of many women household members, typically, the spouse of household head or one adult woman member. Peterman et al. (2015) have highlighted that involvement in the intra-household decision-making process can be considered an intrinsically meaningful empowerment dimension because all household members within a household have that right. In this case, because decisions are made through bargaining among all eligible household members, gender specific preferences are obtained and assessed in a more meaningful way than simply focusing on husband and wife's decisions (Sariyev et al., 2020a). Consistent with these recent insights, this study considered all household member's participation in the decision-making process to create an index capturing women's participation in household's decision-making (WPDM).

Studies examining the effect of household's characteristics particularly age, experience and education on technical efficiency of aquaculture production have generated mixed results. Man-headed households exhibit higher technical efficiency compared to woman-headed households because men tend to have better access to formal institutions and extension services than women due to societal and cultural norms (e.g., Oluwatayo and Adedeji, 2019). The effect of total household expenditure appears ambiguous as it depends on fish producers' preferences for investing capital into the aquaculture sector as opposed to the non-aquaculture sector (Alam et al., 2012). Access to extension services has been shown to positively influence technical efficiency (Cinemre et al., 2006; Iliyasu and Mohamed, 2016; Singh et al., 2009). Extension advice generates knowledge exposure necessary for optimal input use and improvement in general management of the farm. Evidence about the effect of pond size on technical efficiency is mixed; a few studies such as Cinemre et al. (2006) and Onumah et al. (2010) found a negative correlation while Tan et al. (2011) reported a positive relationship. Dey et al. (2010) indicated that integrated aquaculture and agriculture farming system is an effective production strategy for improving technical efficiency and productivity. Moreover, polyculture would have a positive effect on technical efficiency, as it encourages efficient input use and takes advantage of the beneficial interactions between compatible species cultured in the same pond (Halwart and Gupta, 2004). Adopting climate change adaptation practices such as water and soil conservation practices, improved irrigation systems and changes in cropping schedule and varieties, against climate change manifestations such as flooding, droughts and frosts, has been shown to correlate with increased productivity and technical efficiency (Roco et al., 2017).

Two popular techniques, namely the stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are commonly used for the technical efficiency analysis. SFA is superior over DEA because it includes statistical noise into the frontier and allows for statistical tests on the efficiency estimates. However, the results of SFA can be sensitive to the parametric form chosen (Chavas et al., 2005). In contrast, DEA is preferred at times because it does not require any explicit functional form for the production function. The main advantage of DEA is that the technical inefficiency measure can be estimated for each observation (Forsund et al., 1980). In addition, the DEA method can not only identify sources and amounts of inefficiency in each input and output for each farm but also the efficient set used as a reference for these evaluations (Cooper et al., 2010). In the DEA approach, the efficiency of decision-making units is measured in two ways: input-oriented model and output-oriented model. Due to the scarcity and increase of inputs prices as well as the restrictions on land use for small-scale aquaculture in Myanmar, input-oriented DEA method was used in this study to measure the minimum input level of the theoretically efficient farm at the given actual level of output with variable returns to scale (VRS) as proposed by Banker et al. (1984). Factors such as constraints on land use, inputs use and other socioeconomic limitations of fish farmers may cause the farm not to operate at an optimal scale practically. Therefore, in aquaculture studies, particularly in developing countries, VRS DEA model for production technology is often assumed (Zongli et al., 2017).

Two common types of conventional DEA techniques from the input-oriented approach were applied in this study: radial and non-radial. On the one hand, the radial DEA model gives the same specified proportional changes by which all outputs (inputs) are increased (reduced) simultaneously to become efficient and does not take into account slacks in resource usage directly. On the other hand, a non-radial DEA model known as the slack-based measure (SBM) of technical efficiency, gives a different proportion and can deal directly with slacks in the efficiency estimation (Tone, 2001). Simar and Wilson (2000, 2007) indicated that due to deterministic nature of conventional DEA, efficiency scores estimated are biased and serially correlated, consequently generating invalid statistical inferences in the second stage of the regression analysis. The efficiency scores estimated by finite samples are thus subject to sampling variations of the estimated frontier. To overcome the above-mentioned issues of the conventional DEA technique, Simar and Wilson (1998, 2000, 2007) have developed bootstrap procedures to introduce statistical foundation to the nonparametric frontier model.

The objectives of this study are: (1) to measure the technical efficiency of small-scale aquaculture using radial, non-radial and two-stage double bootstrap data envelopment analysis (DEA) methods; and (2) to examine the association between WPDM and technical efficiency.

2. Methodology

2.1. Data collection

Our analysis relied on data from 440 small-scale aquaculture households collected during an on-farm aquaculture performance assessment baseline survey in 2019 under the project “Scaling systems and partnerships for accelerating the adoption of improved tilapia strains by small-scale fish farmers (SPAITS).” The project was implemented by WorldFish in collaboration with Myanmar’s Department of Fisheries (DOF) and University of Hohenheim. A combination of stratified, purposive and random sampling techniques was used to select study respondents. First, the Ayeyarwaddy Delta Region was selected as the study area because it is the main fish producing region in Myanmar. Second, three townships in the region namely Daydaye, Kyaiklatt, and Phyapon were purposely selected for the study. In these townships, another WorldFish’s project “Promoting the sustainable growth of aquaculture in Myanmar (MYFC)” has carried out activities to support the households to engage in small-scale aquaculture. During the SPAITS project baseline survey period, the MYFC project had five batches of farmers. However, farmers in one of the batches were new to aquaculture and had not completed a fish farming cycle at the time of the survey. Therefore, these farmers were excluded from the sampling frame. A total of 1776 fish farming households in the remaining four batches of the MYFC project formed the sampling frame from which a random sample of 440 households was selected for the study. Among the total sampled households, 17 households had no harvest in the previous fish farming cycle and were dropped from the analyses, leaving a total of 423 households for the analysis.

The survey was conducted from May to July 2019. The questionnaire was pre-designed and pre-tested during an enumerator training held in May 2019. The questionnaire was developed in English, translated into Burmese, and programmed in Open Data Kit (ODK) for mobile data collection. The questionnaire consisted of different modules for an integrated aquaculture performance assessment, including household characteristics, biological, social, economic, and environmental aspects of fish farming, and the livelihoods and well-being of the fish farming households.

2.2. Description of study variables

Variables used in the bootstrapped truncated regression model were selected based on most aquaculture studies in developing countries. Household characteristics such as age (in years), household head gender (man = 1, woman = 0), and farming experience of household head (in years), education level of household members (years of formal education), household’s annual total expenditure (USD), access to extension services (if a household had access = 1,otherwise = 0), and climate shocks (if fish farming was affected by climate shocks in the previous production cycle = 1, otherwise = 0) were included in technical efficiency analysis. Aquaculture production practices applied by farmers in the study area such as, integrated aquaculture-agriculture (IAA) (household practiced IAA = 1, otherwise = 0), polyculture (household practiced polyculture = 1; otherwise = 0), climate change adaptation practices (household implemented any strategy to address climate risks = 1; otherwise = 0), and pond size (ha) were used to capture the impact of technology and management practices on the technical efficiency of fish farming. In regard to the social aspect of the aquaculture sector, WPDM as a measurement of women’s empowerment was expected to influence the technical efficiency positively. This aspect may also directly influence agricultural productivity through household members’ ability to organize and allocate resources (Mcpeak and Doss, 2017; Sell and Minot, 2018).

2.3. Methods and empirical models

In this study, an input-oriented approach DEA model was adopted with the aim of using minimum feasible amount of inputs while retaining at the given output level. To estimate the overall and input-specific technical efficiency scores, this study applied radial and non-radial or slack-based DEA models. In addition, due to the biased and serially correlated technical efficiency scores derived from the conventional DEA model criticized by Simar and Wilson (2007), a two-stage double bootstrap DEA technique was applied to estimate bias-corrected efficiency scores as well as the determinants consistently.

2.3.1. Conventional DEA models (radial and non-radial or slack-based measure (SBM))

Given the output Y (fish harvested) and inputs set (seed, feed, fertilizer, labor and other miscellaneous costs), the input-based technical efficiency of the DEA framework for the jth farms, TE_j is defined as

$$TE_j = \min_{\theta_j,\lambda} \theta_j \tag{1}$$

subject to

$$Y_j \leq Y\lambda,$$

$$\theta_j X_j \geq X\lambda,$$

$$\lambda \geq 0$$

$$\sum_{j=1}^{N} \lambda_j = 1$$

Where θ_j is the technical efficiency score with $0 \leq \theta_j \leq 1$. If $\theta_j = 1$, the farm is technically efficient. The vector λ is an N x 1 vector of weights that defines the linear combination of the peers of the j^{th} farm. The first constraint in Eq. (1) is with respect to the output of small-scale fish farming. Y_j, tonnes (t) of fish harvested per farm in previous production cycle, is the actual level of output of the j^{th} farm compared with the theoretically efficient farm ($Y\lambda$) output vector. The second constraint concerns the inputs of small-scale fish farming. Five main inputs used per farm in previous production cycle, namely seed (number of fingerlings), feed (t), fertilizer (t), total labor (person-days) and other miscellaneous costs (USD) are incorporated into the VRS DEA model in Eq. (1). $\theta_j X_j$ represents the actual level of input used by the j^{th} farm multiplied by its level of efficiency (θ_j). $X\lambda$ is the minimum input use of the theoretically efficient fish farms, given the actual level of output produced by the j^{th} farm. If the solution in Eq. (1) is smaller than one, the quantity of input used by that particular fish farm can be reduced to as low as $X\lambda$ to produce the same level of output. If the solution in Eq. (1) turns out to be $\theta_j = 1$, that particular small-scale fish farm's inputs level is as small as the level of input used by the theoretically efficient farms at a given the same level of output. The third constraint in Eq. (1) is the convexity constraint, $\sum_{j=1}^{N}\lambda_j = 1$, for assuming the variable returns to scale (see for further details in Coelli et al., 2005). The model, as mentioned above, intends to proportionately reduce all inputs with a given output level. The efficiency score derived from this model is called the radial measure of technical efficiency score, but it cannot estimate a comprehensive efficiency measurement and lacks discriminatory power for individual input (Tone, 2001).

In order to capture the percentage of reduction in the use of any individual input, a non-radial DEA or slack-based measure (SBM) of technical efficiency model was applied, the mathematical properties of which can be found in Tone (2001). The SBM of technical efficiency method was expressed as follows:

$$min_\rho = \frac{1-(1/m)\sum_{i=1}^{m} S_i^- / x_{ik}}{1+(1/s)\sum_{r=1}^{s} S_r^+ / y_{rk}} \tag{2}$$

subject to

$$x_{ik} = \sum_{j=1}^{n} x_{ij}\lambda_j + S_i^-, \quad i = 1, \ldots, m$$

$$y_{rk} = \sum_{j=1}^{n} y_{rj}\lambda_j - S_r^+, \quad r = 1, \ldots, s$$

$$\lambda_j \geq 0, \quad j = 1, \ldots, n$$

$$S_i^- \geq 0, \quad i = 1, \ldots, m$$

$$S_r^+ \geq 0, \quad r = 1, \ldots, s$$

Where, ρ denotes the SBM of technical efficiency of decision making units (DMUs) associated with s output set y_{rk} (s = different types of fish species) and m input set x_{ik} (m = seed, feed, fertilizer, labor, other miscellaneous costs); λ_j is a non-negative vector that allows the production possibility set construction for DMUs j; n is the number of DMUs ($j = 1,\ldots n$); S_i^- and S_r^+ are denoted as slacks associated with inputs x (input access) and output vector Y *(output shortfalls)*, respectively. $S_i^- = 0$ implies no input excess and $S_r^+ = 0$ implies no output shortage for all i and r. We have the following formula to calculate any particular input efficiency derived from input-oriented SBM technical efficiency model (Haider et al., 2019):

$$\text{Input} - \text{specific technical } \mathit{efficiency} = \frac{\text{OIU}}{\text{AIU}} = \frac{\text{AIU} - \text{IS}}{\text{AIU}} \tag{3}$$

where OIU is the optimal input use or input target, AIU is the actual input use, and IS is the input's slacks value. In the slacked-based model, the percentage of reduction in each input to close the production frontier was captured by their associated slacks.

2.3.2. Bootstrap data envelopment analysis (DEA) procedure

Bootstrapping is a method of testing the reliability of a data set by creating a pseudo-replicate data set. The simple idea of the bootstrap procedure is resampling the data with replacement and simulating a true sampling distribution by mimicking the data generating process. The reason for using the bootstrap procedure is to generate bias-corrected technical efficiency (BCTE) scores and obtain consistent statistical inference within models explaining efficiency scores (see details in Simar and Wilson, 1998, 2000; Badunenko and Mozharovskyi, 2016). Following Simar and Wilson (2007) modified by Badunenko and Tauchmann (2019), the double bootstrap procedure was used to estimate the technical efficiency scores from the input-oriented approach and identify the factors influencing the technical efficiency scores. The double bootstrap procedure is shown in details in Appendix A.1. Two main points should be considered when applying the double bootstrap procedure. First, steps 1–4 (the first loop of the double bootstrap DEA) are employed to estimate the bias-corrected efficiency scores. Second, the truncated regression analysis is conducted in steps 5–7 (the second loop of the double bootstrap DEA) to explain the factors influencing the bias-corrected efficiency scores.

2.3.3. Principal component analysis (PCA) to generate the women's participation in decision-making index (WPDMI)

Although there are different dimensions of women's empowerment, this study focused on the decision-making dimension only as a measurement of women's empowerment. In order to represent the decision-making in different decision domains, the data included the information about the decision related to many household level activities. Among the activities, priority was given to the decisions that are relevant for most of the selected households because all households are not engaged in the same activities. The index in this study was generated from seven decision variables related to input use in fish production, harvested fish use, quantity and type of food consumed, land allocation, fish income, crop income, and livestock income allocation. In this regard, selected decisions were made by more than 90% of the selected households except decision in livestock income allocation (60% of the households) and therefore it reflects the most important decision-making variables for the households in the study area. In order to collect the accurate and required information, the respondents were asked who made the decision in the selected variables. This was followed by naming the household members and the response was cross-validated with the household roster.

To generate an index using PCA technique, households were first assigned weights related to their respective decision domains based on women's participation in the decision-making processes. Following Sariyev et al. (2020a), weights for each decision-making variable were calculated by the ratio of the number of women decision makers within the household to the total number of decision-makers in each decision domain. These assigned weights range between 0 and 1, with 0 indicating no women participation and 1 indicating only women participation. Table 1 summarizes the different weights of each decision domain.

3. Empirical results and discussion

3.1. Descriptive statistics of the data

Descriptive statistics of the variables included in the technical efficiency and regression analysis are presented in Table 1. The average household head was 52 years old and had 3 years of small-scale fish farming experience. Both men and women household members had an average education level of 7 years. The total annual expenditure of households was 825.45 USD.[1] About 93% of the sampled households were man-headed.

The average quantity of fingerlings stocked, feed, fertilizer, labor used and other miscellaneous costs incurred per farm during the previous fish production cycle, were estimated at 478 fingerlings, 0.07 t,

[1] 1 USD = 1518.34 MMK (July 31,2019).

Table 1
Descriptive statistics for variables used in the analysis.

Variables	Mean	Std. Dev
Demographic characteristics of households		
Household head gender (man = 1, woman = 0)	0.93	0.27
Age of household head (years)	52	12.18
Education level of men household members (years)	7	2.57
Education level of women household members (years)	7	2.47
Fish farming experience (years)	3	2.24
Extension services (access = 1, no access = 0)	0.86	0.35
Total household expenditure per year (USD)	825.45	947.44
Aquaculture production characteristics		
Pond size (ha)	0.04	0.06
Total fish output harvested (t) per farm	0.13	0.17
Total fingerlings stocked (number) per farm	478.42	306.39
Total feed use (t) per farm	0.07	0.10
Total fertilizer use (t) per farm	0.06	0.10
Total labor use (person-day) per farm	276	103.19
Other miscellaneous costs (USD) per farm	11.92	15.43
Integrated fish farming (yes = 1, no = 0)	0.56	0.50
Polyculture (yes = 1, no = 0)	0.02	0.15
Household adopted mitigation strategies against climatic shocks (yes = 1, no = 0)	0.75	0.44
Climatic shocks affected fish farming in previous production cycle (yes = 1, no = 0)	0.57	0.50
Women's participation in decision-making activities		
Input use in fish production (%)	0.13	0.30
Harvested fish use (%)	0.28	0.38
Land allocation (%)	0.17	0.30
Type and quantity of food consumed by household (%)	0.72	0.39
Fish income allocation (%)	0.37	0.36
Crop income allocation (%)	0.38	0.35
Livestock income allocation (%)	0.43	0.28

Note: 1 USD = 1518.43 MMK (July 31,2019).
Source: Own calculations.

0.06 t, 276 person-days and 11.92 USD, respectively. The average harvested quantity of all fish species per farm in the previous cycle was 0.13 t. Regarding fish farming practices, 56% of fish farming households implemented integrated fish farming but only 2% of those households practiced the polyculture system. Three-quarters (75%) of sampled households had observed climate change events, including flood, erratic rainfall, storms/cyclones and extreme high temperature. These households also implemented adaptation strategies such as harvesting fish early, upgrading fish ponds, monitoring water quality, exchanging pond water, and changing their farmed fish compositions. Results further show that 57% of households' farm were actually affected by those climate shocks in the previous fish production cycle. Among the decision-making variables, women were most involved in those related to the type and quantity of food consumed by the household, followed by income allocation from livestock, fish, and crop production.

3.2. Estimates of technical efficiency of small-scale aquaculture farms through radial DEA, non-radial DEA or SBM, and bootstrap DEA in study area

Results of technical efficiency (TE) analysis (radial DEA, non-radial DEA and bootstrap DEA techniques) are presented in Fig. 1. The average technical efficiency score under the radial DEA analysis was 0.55, which implies that the fish farming households in this study could reduce approximately 45% of their input use without changing their output level. However, the magnitude of the non-radial efficiency score was at an average level of 0.40, so the feasible input reduction was 60%. Theoretically, the average TE derived from the radial model was 15% higher than that obtained through non-radial method, which means radial TE overestimates the efficiency level because it does not take into account the slacks in efficiency estimation and it lacks discriminatory power.

The results of the bootstrap DEA in Fig. 1 reveal that the overall bias-corrected technical efficiency (BCTE) score was 0.44, which highlights that there is substantial potential for input reduction at 56%. These findings reveal that the radial DEA model efficiency scores are overestimated if the sample bias is not adjusted. By the confidence interval of BCTE scores, it is distinct that the gap between the lower (0.41) and upper (0.54) boundary was comparatively small. Moreover, while the BCTE scores were within the confidence interval, the radial DEA efficiency scores were not within this interval due to the sample bias (Simar and Wilson, 2007). Furthermore, the bias-variance test statistic was far above one for all BCTE scores, confirming the accuracy and reliability of bootstrap DEA estimates. These particular results show that this efficiency score is statistically reliable and characterizes well the data generating process. Therefore, the bootstrap procedure can minimize the sample sensitivity.

As presented in Fig. 1, most of the fish farming households fell within the radial technical efficiency scores range of 0.3–0.6 (59%), while 15.37% of the sampled households registered technical efficiency scores between 0.8 and 1. Additionally, 47% of sampled households recorded non-radial technical efficiency score range of 0.3–0.6 and only 9.33% of sampled households operated with the efficiency score between 0.8 and 1. Moreover, by the BCTE scores, 69% of fish farming households' efficiency score ranged from 0.3 to 0.6, but only 2.6% of sampled households' technical efficiency scores recorded within the range of 0.8–1. The results highlight that many fish farms in this analysis are relatively inefficient, indicating that there is still room to improve fish farm technical efficiency even if current input levels and technology are maintained.

Table 2 presents the results of Kolmogorov-Smirnov tests for the equality of technical efficiency distributions by major farmed fish species and production systems. Among the most common fish species groups, there were statistically significant differences at the 5% and 10% levels, respectively, between the radial and bias-corrected efficiency scores except for rohu and pangasius group.[2] There were significant differences at 10% and 5% levels, respectively, between the radial and non-radial TE scores of sampled households in the Daydaye and Phyapon townships. In addition, all TE scores in polyculture (including rohu and pangasius) and sediment removal groups were statistically significantly at the 5% and 10% levels, respectively. The radial and bias-corrected efficiency scores in the integrated farming system groups were statistically significant at 10% level, respectively.

3.3. Slack variable analysis results

A slack variable refers to the deficit output or excess input used in fish production, measured. However, assuming fish farms are operating in a similar environment, setting appropriate input targets for lower efficiency farms helps the farms to reach or be close to the production frontier in comparison with the farms on the frontier. Input targets (projected point) refer to "the total amount of inputs adjustment required for inefficient DMUs to operate on the production frontier" (Tone, 2001). The actual input use is higher than an input target for an inefficient firm. Input slacks refer to "the differences between the input target and actual input amount" (Ramanathan, 2003).

Our results show that the estimates for efficiency in fingerling and feed inputs were 0.68 and 0.36, respectively, which implies that average fingerling and feed use could be reduced by 32% and 64%, respectively, and still produce the current level of output. Generally, fish farming households assume that the higher the stocking density, the higher the output. In reality, overstocking reduces space availability, creating

[2] The group in this sentence represents the household group. E.g., rohu group includes the households who stocked rohu species in their farms and pangasius group includes households who stocked pangasius species in their farm and then compare the TE scores of two different household groups (rohu and pangasius).

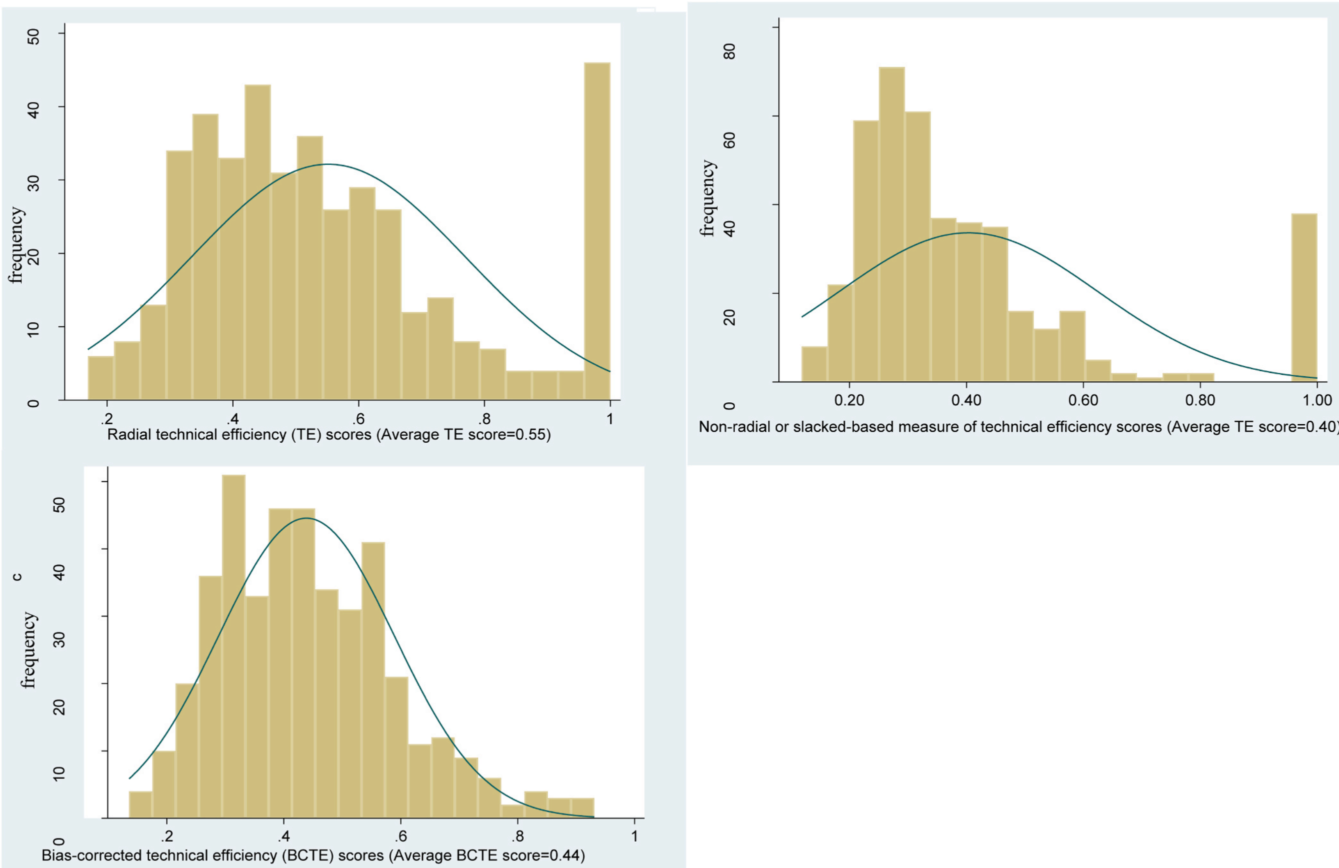

Fig. 1. Frequency distribution of technical efficiency scores in small-scale aquaculture using the radial, slack-based, and bias-corrected methods.

Table 2
Kolmogorov-Smirnov test for the equality of distribution between pairs of fish species and study area.

	Radial technical efficiency		Non-radial technical efficiency		Bias-corrected technical efficiency	
	Test value	P-value	Test value	P-value	Test value	P-value
Fish species*						
F1 & F2	0.07	0.78	0.08	0.54	0.08	0.58
F1 & F3	0.20	0.06	0.16	0.19	0.22	0.03
F2 & F3	0.21	0.04	0.12	0.56	0.21	0.04
Study area**						
A1 & A2	0.14	0.08	0.16	0.03	0.09	0.49
A1 & A3	0.13	0.60	0.16	0.29	0.14	0.52
A2 & A3	0.16	0.25	0.12	0.53	0.17	0.18
Facility type*** (P&C)	0.13	0.56	0.12	0.63	0.14	0.53
Integrated fish farming	0.13	0.05	0.09	0.26	0.12	0.06
Polyculture	0.50	0.02	0.47	0.04	0.48	0.03
Sediment removal	0.16	0.01	0.13	0.07	0.13	0.06

Notes: The null hypothesis is the equality of distribution.
*The most common species among the fish farmers in the study area are rohu (F1), pangasius (F2), and silver barb (F3). **A1 = Daydaye, A2 = Phyapon, A3 = Kyaiklatt, ***P = Pond, C = Chang Myaung.
Source: Own calculations.

stress for fish and eventually leading to a high mortality rate (Iliyasu and Mohamed, 2016). Therefore, information on the suitable stocking density is of paramount importance for the success in fish farming because overstocking the fingerlings has adverse effects on fish growth. There are two major implications of the overuse of feed input: increased production costs, which in turn lower profits, and contamination of the fish environment that leads to reduced oxygen levels and higher mortality rates (Iliyasu and Mohamed, 2016). As the sampled fish farming households are smallholders with an average of only 3 years of aquaculture experience, they did not employ recommended stocking densities and feed amounts, which leads to the inefficient use of inputs.

The potential input reduction for the fertilizer was around 70%. All fish farming households applied fertilizer, mostly at the pond preparation stage. Lime, phosphate, and urea are the most commonly used fertilizers for households. Several factors might explain the low fertilizer efficiency level. For example, small-scale aquaculture farmers might not apply recommended or standard fertilizer rates due to the lack of quality and effective extension services. In addition, climate shocks can be the other possible reasons for the lower efficiency level of the farms because only very few households affected by climate shocks are operating their farms at the optimal level. The estimated average labor efficiency score was 0.44, which implies that fish farming households can reduce their use of labor by approximately 56%. Most of the sampled households depend heavily on the family labor use for fish production activities, particularly fish feeding, while a few casual workers are occasionally hired for pond preparation and harvesting. However, an increase in labor use does not necessarily add to the efficiency level of fish farmers. Compared to large-scale fish farming, small-scale fish farming tends to use more labor due to lack of capital-intensive technologies. Therefore, most sampled small-scale farmers require adjustments to achieve labor efficiency. Climate shocks can also be the other possible reasons for the low labor efficiency level of the studied farms. The slack-based efficiency score in the other input costs was found to be reduced around 70%. Among these miscellaneous costs, fuel cost and rent for machinery account for the largest share of these costs.

3.4. Women's participation in decision-making processes of small-scale fish farming households

Our results in Appendix A.3 revealthat most of the decision-making variables had shown strongly significant and positive correlation, supporting the use of PCA. The null-hypothesis of Bartlett's test was rejected (see Appendix A.2). For the results of PCA to be valid, only factors with an eigenvalue greater than 1 were retained in the analysis. The absolute factor loadings of all decision variables were higher than 0.4 (see Appendix A.5), indicating that all are important for the factor, that is, participation in decision making. Moreover, as the final validity test, all decision variables had a Kaiser-Meyer-Olkin (KMO) value higher than 0.6, and the overall KMO value was 0.77, which indicates sampling adequacy. All validity tests yielded the positive results, indicating that the predicted values referring to WPDMI present effectively the information included in the decision variables. The WPDMI was a continuous index between − 1.45 and 2.83. Fig. 2 presents the histogram of WPDMI.

3.5. Determinants of technical efficiency

The estimation results of the bootstrapped truncated regression are presented in Table 3. As the dependent variable represents bias-corrected technical inefficiency scores, hence, a positive (negative) coefficient sign indicates a negative (positive) source of technical efficiency.

Regarding socioeconomic variables of the households, although age, age squared, experience of the household head, access to extension services, household's annual total expenditure and average education level of household members were expected to impact the technical efficiency of their farms, we did not find any linkages between these variables and technical efficiency in different models. Long et al. (2020a, 2020b) and Nguyen and Fisher (2014) also reported an insignificant relationship between education, experience and access to training variables and technical efficiency in Vietnam.

The coefficient of household head gender was negative and statistically significant at the 5% level. This result indicates that man-headed households are associated with higher technical efficiency compared to woman-headed households. A possible reason could be that following the social and cultural norms in the study area, man-headed households are more likely to access quality advisory services delivery through social networks, formal extension, and alternative channels of information than their woman counterparts therefore leading to higher productivity and improved technical efficiency for the farm. Similar results were reported by Alene et al. (2008), Ragasa et al. (2013), Aguilar et al. (2015), Oluwatayo and Adedeji (2019) and Quisumbing et al. (2013). However, the insignificant relationship between formal extension services and technical efficiency of small-scale fish farming can possibly suggests the need for improved quality of aquaculture knowledge diffusion. Ragasa et al. (2013) indicated that the frequency of extension visits may not matter for improved productivity if the quality of advisory services is poor. Perhaps social networks and

Table 3
Bootstrapped truncated regression analysis.

Variables	Coefficient	S.E.
Demographic characteristics of households		
Age of household head (years)	0.003	0.004
Age squared of household head (years^2)	-0.000	0.000
Fish farming experience (years)	0.001	0.003
Extension services (access = 1, no access = 0)	-0.020	0.021
Education level of men household members (years)	-0.003	0.003
Education level of women household members (years)	-0.001	0.003
Log of total household expenditure per year (USD)	-0.005	0.009
Household head gender (man = 1, woman = 0)	-0.090	0.040**
Women's participation in decision-making index	-0.017	0.008**
Aquaculture production characteristics		
Integrated fish farming (yes = 1, no = 0)	-0.012	0.016
Polyculture (yes = 1, no = 0)	-0.106	0.052**
Pond size groups		
Group 2	-0.045	0.017***
Group 3	-0.063	0.018***
Household adopted mitigation strategies against climatic shocks (yes = 1, no = 0)	-0.041	0.020**
Climatic shocks affected fish farming in the previous production cycle (yes = 1, no = 0)	0.012	0.020
_cons	0.629	0.154***
Sigma	0.145	0.006***
Observations	423	

Notes: P-values less than 0.1, 0.05, and 0.01 correspond to *, **, and ***, respectively. S.E. is the bootstrapped standard error.
*Pond size was split into three groups: group 1 (< < 0.02 ha), group 2 (0.02–0.04 ha), and group 3 (>0.04 ha).
Source: Own calculations.

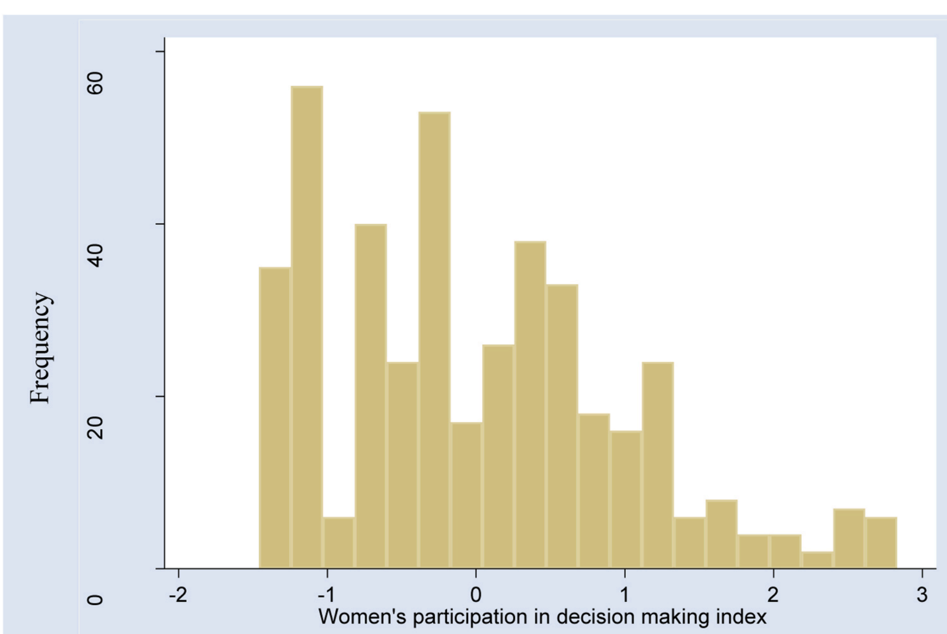

Fig. 2. Histogram of women's participation in decision-making index.

alternative channels of information such as radio or agro dealers could allow households to not only have exposure to innovations and best management practices but also ensure they acquire the skills required for proper implementation of the practices on-farm.

As expected, WPDM was positively and significantly associated with technical efficiency at the 5% level. Women's participation in decision-making process within the household raises their voice within the household and increases their access to production resources, which in turn positively affects agricultural productivity (Adeyeye et al., 2019). The strong bargaining power that results in intensive participation in decision-making activities may directly influence the technical efficiency and productivity of fish farming through its effect on the household members' ability to allocate and organize productive resources optimally (Diiro et al., 2018). Such bargaining power reduces gender inequality by empowering women with more control over decision, which, in turn affects their lives by enabling them to allocate more resources to their preferences (Doss, 2013). In addition, women's participation in decision-making tends to have "spillover" to the farms operated by others within the households by sharing the information or pooling resources because all household members may have different preferences that they would bring to the household decision-making processes. Household head gender as the main variable of interest does not capture the information on intra-household decision-making. Analysis by Seymour (2017) suggests that both man and jointly managed plots in Bangladesh have higher technical efficiency when empowerment gap is reduced.

Among the fish farming systems, polyculture has a positive effect on technical efficiency and was statistically significant at the 5% level. Regarding the environmental aspect, adoption of adaptation strategies such as harvesting fish early, upgrading fish ponds, monitoring water quality, exchanging pond water and changing their farmed fish composition, against climatic shocks, such as flooding, erratic rainfall, storms/cyclones and extreme high temperature, has a positive effect on technical efficiency at the 5% significance level. Farmers who are aware of climate variability are able to make more efficient use of their productive resources by applying the adaptation practices based on their knowledge and understanding of climate change (Ehiakpor et al., 2016). Efficient and moderately efficient farmers are more perceptive of climate change, compared to less efficient farmers (Torres et al., 2019). As documented by Torres et al. (2019) and Roco et al. (2017) the use of climate change adaptation strategies is imperative to sustain and promote agricultural productivity and technical efficiency. Additionally, the sign of the coefficient for pond size is consistent with our expectations. The results show that pond size has a positive impact on technical efficiency that was statistically significant at the 1% level, indicating that fish farming in larger ponds is more efficient than farming in smaller ponds. Due to the economies of scale, expanding the level of output as the pond size increases leads to an increase in input use efficiency with lower production costs.

The findings from this study provide important policy recommendations from different perspectives. To achieve the purpose of increased technical efficiency of small-scale aquaculture in Myanmar, the government and other development organizations should promote dissemination and adoption of the best management practices through quality and effective extension services and provide incentives to small-scale fish farmers for improving the productivity and efficiency of their fish farming. Results also suggest the need for improving the quality of extension services delivery in order to equip farmers with the skills required to implement the practices properly. In addition, cooperation with local or international organizations and research institutes should be encouraged to develop a proper fish feeding formula with good feeding practices that corresponds to the stage of fish growth, culture system, and species types to reduce the current inefficient use of feed because feed is the major input in fish production and constitutes over half of the production costs. Dissemination of information on the suitable fish stocking density through quality extension services and the quality of fingerlings such as genetically improved farmed tilapia (GIFT) or other species and proper size of fingerings are of paramount importance in improving the technical efficiency. This would help fish farms succeed economically and environmentally. Additionally, the policies or intervention programs directed to increase productivity and technical efficiency of small-scale aquaculture should be implemented together with policies designed to encourage women's empowerment. Finally, government and non-government organizations should set up information dissemination programs and training schemes in relation to climate variability to enhance households' understanding and knowledge about this issue in implementing adaptation practices effectively.

4. Conclusion

Our technical efficiency analysis has revealed that small-scale aquaculture households under the study were operating below the production frontier, indicating possibilities of input reduction for improved on-farm aquaculture performance without changing the level of their output. Theoretically, the average TE derived from the radial model is 15% higher than that obtained through non-radial model, which means radial TE overestimates the efficiency level because it does not take into account the slacks in efficiency estimation and it lacks discriminatory power. The results of the bias-corrected TE scores have also revealed that the radial DEA model efficiency scores are overestimated if the sample bias is not adjusted. In addition, our results of the slack analysis have shown that all the inputs used in fish production contain slacks and they could be reduced accordingly.

We found that participation of women in decision-making within the household is associated with increased technical efficiency. To draw lessons from this research finding, we concluded that WPDM is one of the crucial strategies for more efficient resource utilization that maximizes output. Regarding socioeconomic factors, our results show that man-headed households have higher technical efficiency than woman-headed households due to social and cultural norms that favor the participation of the former in social networks. From the evidence presented in this study, as scale of economies exists in Myanmar's small-scale aquaculture sector, small-scale fish farming households could gain higher productivity with more efficient input utilization by increasing their pond size. In addition, different fish farming systems, such as polyculture and adaptation strategies against climatic shocks are another considerable scope of improvement in this sector.

This study has suffered two limitations. First, we were unable to measure the women's empowerment score and Gender Parity Index (GPI) by using comprehensive measurement of women's empowerment such as WEAI and WELI due to the lack of information on the indicators of these techniques. To measure women's empowerment using these methods, a constructed questionnaire would have to be used for the domains of empowerment and to ask the respondents of both genders particularly main man and woman decision-makers separately. Therefore, future women's empowerment studies could consider using both WEAI and WPDMI methods to analyze the differences and complementarities between these two indicators of empowerment in aquaculture. Second, the study generates important insights about the correlation between WPDM and TE in aquaculture, but unobserved heterogeneity prevalent in non-experimental studies such as ours means we cannot infer causality.

CRediT authorship contribution statement

Yee Mon Aung: Conceptualization, Writing – original draft, Methodology, Data collection, Formal analysis. **Manfred Zeller**: Conceptualization, Supervision, Reviewing and editing manuscript. **Ling Yee Khor**: Conceptualization, Supervision, Reviewing and editing manuscript. **Nhuong Tran**: Funding acquisition, Project administration, Conceptualization, Supervision, Contribution to research design, Coordination of data collection, Review and editing manuscript. **Kelvin**

Mashisia Shikuku: Conceptualization, Contribution to research design, Training enumerators, Reviewing and editing manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research is a contribution to the Consultative Group on International Agricultural Research (CGIAR) Research Program on Fish Agrifood Systems (FISH). Funding support to the study was provided by the German Federal Ministry for Economic Cooperation and Development (BMZ) through the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ), on a project entitled "Scaling Systems and Partnerships for Accelerated Adoption of Improved Tilapia Strains (SPAITS)" [grant number 81219436], and the German Academic Exchange Service (DAAD). We gratefully acknowledge the logistics and technical support from WorldFish Penang and Myanmar offices. We are thankful to Dr. Cynthia McDougall for her insightful comments and suggestions, Dr. Emily McNulty for proofreading the article and Cheong Kai Ching for his data quality supervision during the survey. The views expressed in this document cannot be taken to reflect the official opinions of these organizations.

Appendices.

Appendix A.1

Step (1): Estimate the technical efficiency (θ_j) for all small-scale fish farms in the sample data set j = 1, ……, n using Eq. (1).

Step (2) Use the method of maximum likelihood to obtain coefficient estimates $\hat{\beta}$ and an estimate for variance parameter $\hat{\sigma}$ in the truncated regression of θ_j on Z_j when $\theta_j > 1$.

Step (3): For each j = 1….,n, repeat the following four steps (3.1–3.4) $B_1 = 2000$ times to yield a set of bootstrap estimates $\hat{\theta}_j^b$, with b = 1, ……,B_1.

3.1 For each j = 1, ….,n, an artificial error term $\hat{\varepsilon}_j$ is drawn from the truncated N(0, $\hat{\sigma}$) distribution with the left truncation at 1-$Z_j\hat{\beta}$

3.2 For each j = 1, ….,n, compute the artificial efficiency scores $\hat{\theta}_j = Z_j\hat{\beta} + \hat{\varepsilon}_j$.

3.3 Constructing an artificial data set with input quantities $\left(\hat{X}_j = \theta_j/\hat{\theta}_j\right)X_j$ and output quantities ($\hat{Y}_j = Y_j$).

3.4 Using the artificial data set generated in step 3.3.and Eq. (1), as reference set in a DEA that yields the artificial efficiency score estimates $\hat{\theta}_j^b$ for each original DMU j = 1,……,n.

Step (4): For each j = 1, …….n, calculate a bias corrected efficiency score $\hat{\theta}_j^{bc}$ as $\hat{\theta}_j - \left(\frac{1}{B_1}\sum_{b=1}^{B_1}\hat{\theta}_j^b - \hat{\theta}_j\right)$.

Step (5): Run a truncated regression of $\hat{\theta}_j^{bc}$ on Z_j to obtain coefficient estimates $\hat{\hat{\beta}}$ and an estimate for variance parameter $\hat{\hat{\sigma}}$ by maximum likelihood.

Step (6): Repeat the following steps 6.1–6.3 with $B_2 = 2000$ times in order to obtain a set of bootstrap estimates ($\hat{\hat{\beta}}^b$, $\hat{\hat{\sigma}}^b$), with b = 1,……., B2.

6.1 For each j = 1, ….,n, artificial error $\hat{\hat{\varepsilon}}_j$ is drawn from the truncated N(0, $\hat{\hat{\sigma}}$) distribution with left-truncation at 1-$Z_j\hat{\hat{\beta}}$

6.2 For each j = 1, ….,n, compute the artificial efficiency scores $\hat{\hat{\theta}}_j = Z_j\hat{\hat{\beta}} + \hat{\hat{\varepsilon}}_j$.

6.3. Run a truncated regression of $\hat{\hat{\theta}}_j$ on Z_j to obtain bootstrap estimates $\hat{\hat{\beta}}^b$ and $\hat{\hat{\sigma}}^b$, by maximum likelihood.

Step (7): Use bootstrap estimates $\hat{\hat{\beta}}^b$ and $\hat{\hat{\sigma}}^b$ and the estimates $\hat{\hat{\beta}}$ and $\hat{\hat{\sigma}}$ generated in Step (5) to construct the confidence intervals and standard errors for β and σ_ε. The (1- α) percent confidence interval of the jth element of vector β is constructed as the $Pr\left(-b_{\frac{\alpha}{2}} \le \hat{\hat{\beta}}^b - \hat{\hat{\beta}} \le -a_{\alpha/2}\right) \approx 1-\alpha$ such that the estimated confident interval for β_j is $\left[\hat{\hat{\beta}} + a^*_{\alpha/2}, \hat{\hat{\beta}} + b^*_{\alpha/2}\right]$.

Results of the principal component analysis.

Appendix A.2 Bartlett test of sphericity

factortest DM_inputuse DM_harvestuse DM_nutrition DM_landallocation DM_fishincome DM_cropincome DM_livestockincome	
Determinant of the correlation matrix	Det = 0.064
Bartlett test of sphericity	Chi-square = 1149.247
	Degrees of freedom = 21
	p-value = 0.000
	H0: variables are not intercorrelated
Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy	KMO = 0.77

Note: DM = Decision-making.
Source: Own calculations.

Appendix A.3 Correlation of decision variables

	DM_inputuse	DM_harvestuse	DM_nutrition	DM_land allocation	DM_fish income	DM_crop income	DM_livestock income
DM_inputuse	1						
DM_harvestuse	0.527***	1					
DM_nutrition	0.129***	0.305***	1				
DM_landallocation	0.489***	0.381***	0.194***	1			
DM_fishincome	0.298***	0.576***	0.313***	0.217***	1		
DM_cropincome	0.288***	0.537***	0.304***	0.389***	0.776***	1	
DM_livestockincome	0.214***	0.395***	0.276***	0.296***	0.526***	0.607***	1

Note: P-values less than 0.1, 0.05, and 0.01 correspond to *, **, and ***, respectively.
Source: Own calculations.

Appendix A.4 Factor analysis of decision variables

Factor	Eigenvalue	Proportion
Factor1	3.385	0.484
Factor2	1.121	0.160
Factor3	0.820	0.117
Factor4	0.665	0.095
Factor5	0.461	0.066
Factor6	0.362	0.052
Factor7	0.186	0.027

Source: Own calculations.

Appendix A.5 Factor loadings and KMO results of the decision variables

Variable	Factor loading	KMO
DM_inputuse	0.585	0.704
DM_hrvestuse	0.785	0.834
DM_nutrition	0.475	0.899
DM_landallocation	0.583	0.690
DM_fishincome	0.808	0.725
DM_cropincome	0.845	0.729
DM_livestockincome	0.703	0.892
Extraction method: Principal Component Analysis (PCA)		
Overall KMO: 0.77		

Source: Own calculations.

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