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# Impact of Farm Management Training Programme on Income and Expenditure of Aquaculture Farmers in Minor Irrigation Ponds: A Case Study in Odisha

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ABSTRACT

The Odisha government imparts residential training to the fish farmers from time to time under different state and central government schemes whose actual well-being impact has never been evaluated. In line with this, the present study assessed the direct influence of such training on the well-being of the aquaculture farmers, measured in terms of household income, contribution of fish farm income, and monthly consumption expenditure on food. The study randomly sampled cross-sectional data of 194 farmers from select districts of Odisha and employed propensity score matching (PSM) model as a way of controlling selection bias. The findings showed significant improvement in the household income, proportion of fish farm income, and monthly consumption expenditure, respectively, by log of 0.31-0.34, 23.07-23.67 percentage points, and INR 643-721 among the trained group. Overall, the findings of the study suggest intensification of the training programme in Odisha for sustainable aquaculture sector development and the welfare of the farmers.

**Keywords: Aquaculture, training, impact, propensity score matching, Odisha**

**JEL codes: Q01, Q12, Q13, Q38, O15**

## I

## INTRODUCTION

The aquaculture sector is recognized as having massive potential to double farmers' income and provide food and nutritional security (Argade et al., 2023). As of 2016, India's potential for marine fish production was only 4.5 million ton by exploiting 80 percent of the resources, and there is little scope to stretch further (Ragasa et al., 2022; FAO, 2016). Laying institutional support to small-scale aquaculture in terms of training and capacity building programmes for increased productivity and profitability of the farmers is a pressing need. Dickson et al. (2016) in the Egyptian context showed that aquaculture training contributed to increased production and incomes, although there are issues of selection bias and rigor in the impact evaluation. Some other empirical research (such as Blume et al., 2010; Tai, 2006; Kumar et al., 2024) noted that effective training can increase the knowledge, skills and abilities (KSAs) of the trainees for organizational benefit, however, Gupta et al. (2016) stressed that its effectiveness is based on the willingness of the head of the family to translate the learning into action. Studies also showed that demonstrating the profitability of improved management practices tends to encourage their adoption by fish farmers, which will both further increase farm profits and

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protect the environment (Ansah and Frimpong, 2015; Poot-López et al., 2014; Dickson et al., 2016).

The adoption of improved management practices has been widely promoted from the point of view of improving the environmental performance of fish farms and is often aligned with the introduction of certification schemes such as global GAP or Aquaculture Stewardship Council (Frimpong et al., 2014; Dickson et al., 2017). Kassam and Dorward (2017) showed in their study in Ghana that non-poor small-scale pond fish farmers who have been trained and/or use improved management practices are found to hold the most potential to impact poverty indirectly through realizing growth in the farming economy. These indirect impacts are higher than the direct impacts on poor small-scale fish farmers and the indirect impacts from the small and marginal enterprises (SMEs). This may be the cage because for many adopters of rural small-scale aquaculture, this is a supplementary activity mainly for providing extra income, food, and a strategy for diversification (Toufique & Belton, 2014; Mulokozi et al., 2020). It also helps to improve the purchasing power due to income generation from selling fish and creates employment opportunities, which in turn significantly influence food demands and consumption (Belton & Little, 2011; Kassam & Dorward, 2017). Training participation may also have other benefits which cannot be quantified, such as training covering fish health management are found to be associated with lower risk of fish mortality and income loss in the occurrence of fish disease (Ragasa et al., 2022). Thus, given the direct or indirect impact of small-scale aquaculture on the income of the farmers, we should also explore the contribution of institutional support, such as training on better farm management to the income of the farmers by addressing endogeneity and selection bias. This helps to understand the relevance of costly interventions, and the findings contribute to the literature. According to Topno (2012), "training evaluation is the assessment of objectives with outcomes to answer the question of whether training has accomplished its objectives". Baldwin et al. (2009) stressed long before that successful transfer of learning to the workplace is often limited. Therefore, evaluation of training would help in revising programmes and modules to meet large number of goals and objectives (Mann, 1996).

In the Indian context, there are very few studies to empirically assess the impact of farm management training on household wellbeing indicators such as income and consumption expenditure (Bairagya, 2021, Roy et al., 2021, Argade et al., 2023), but to the best of our knowledge most of these studies did not address selection bias. Again, in the eastern Indian state of Odisha regular residential training programmes are held time to time under different schemes of the central and state governments (Figure 1). In fact, many Aquaculture related Women Self Help Groups (WSHGs) underwent several trainings on better management practices (BMPs) in

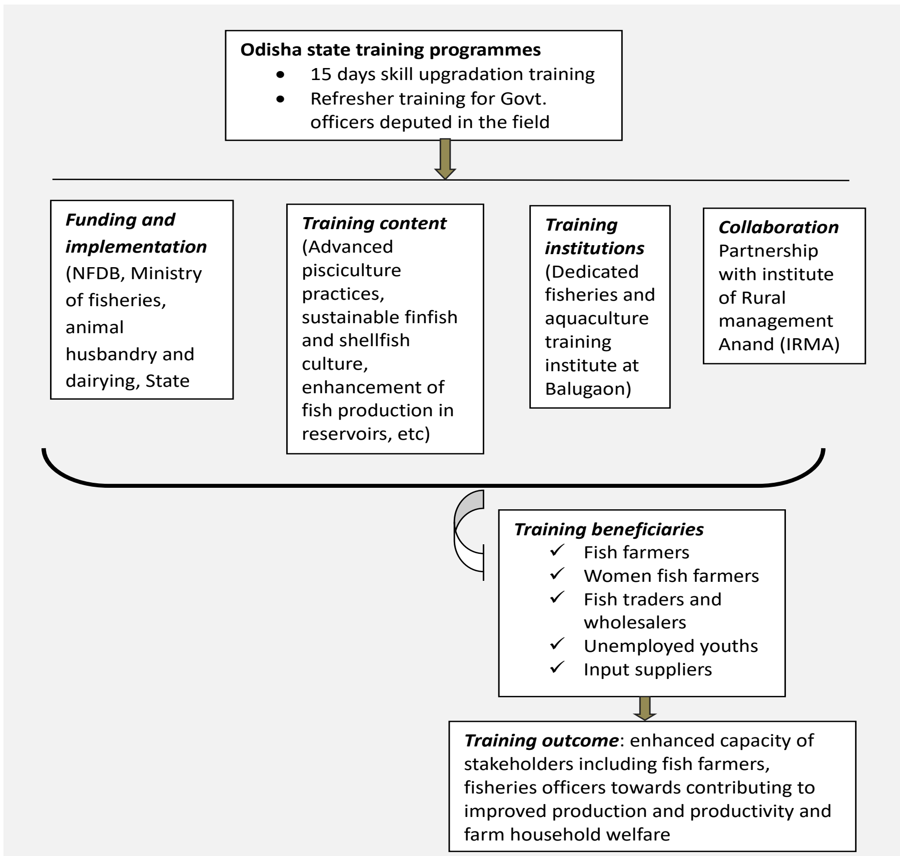


FIGURE 1. FISHERIES AND AQUACULTURE TRAINING PROGRAMME IN ODISHA

Odisha conducted by Fisheries & Animal Resources Department in the recent past for ensuring sustainable and profitable operations through optimal utilization of public water bodies (Dubey et al. 2024). The impacts of these trainings have hardly been observed and documented. Factors associated with income from fish farming and the training participation decision would be a good entry point toward more appropriate aquaculture promotion interventions, which in turn could help increase the diffusion of training programmes for small-scale aquaculture farmers in different parts of Odisha state. Specifically, through this research, we wanted to answer the following questions: (1) What are the socio-demographic factors that influence training participation? (2) Is there a positive association between training participation and income and household consumption expenditure of the farm households? (3) Is there any nexus between the share of fish farm income and farm management training participation of the aquaculture farmers in minor irrigation tanks of Odisha? As empirical evidence often reflects inconclusive effects of aquaculture on alleviating economic destitution of the low-income group farmers (Tran et al., 2023), the present study aims to offer evidence on how small-scale aquaculture can change income and spending on household food items through farmers' capacity building on better farm management activities. To conclude, we used propensity score matching to address selection bias and created a counterfactual approach on observable covariates.

The rest of the paper is organized as follows: Section 2 discusses methodology, detailing data collection and data processing, and the empirical model. While section 3 presents the key results of the empirical model, it also discusses the major findings of the study. Section 4 concludes the paper and gives recommendations in the context of the study sites of Odisha.

## II

## MATERIALS AND METHODS

### *2.1 Data Collection*

The data used for analysis is part of a baseline survey conducted with regards to the aquaculture sub-component of the Odisha Integrated Irrigation Project for Climate Resilient Agriculture (OIIPCRA) funded by the World Bank. The project was implemented in various districts of Odisha, namely, Balasore, Bargarh, Bhadrak, Bolangir, Boudh, Gajapati, Ganjam, Jajpur, Kalahandi, Kandhamal, Keonjhar, Mayurbhanj, Nuapada, Nabarangpur, and Subarnapur (Figure 2). However, during the baseline survey Jajpur District was not considered because of not covering some key project intervention components. The project beneficiaries were the users of minor irrigation ponds, and these ponds were distributed highly sporadically in all the districts. It is for this reason the selection of the respondents using scientific sample selection techniques such as use of Yamane (1967) or Cochran formula was not possible, and challenge was primarily due to larger geography. The study team resorted to random selection of the potential beneficiaries of the project. The selection was assigned to government field officials such as District Programme Managers (DPMs), members of support organizations (SOs), and field officers from partner organizations. Key informant interviews (KIIs) were conducted with district fisheries officers (DFOs) and assistant fisheries officers (AFOs) in each project district to validate the list of surveyed farmers as potential beneficiaries. These beneficiaries are intended to receive training and other physical support with expected results of income augmentation and changes in other household wellbeing. To assess the baseline status of the users of minor irrigation tanks a structured interview schedule was developed, incorporating the relevant questions representing the aquaculture farming systems and household level impact indicators. The questionnaire was pre-tested by interviewing 2-3 aquaculture farmers in each of the

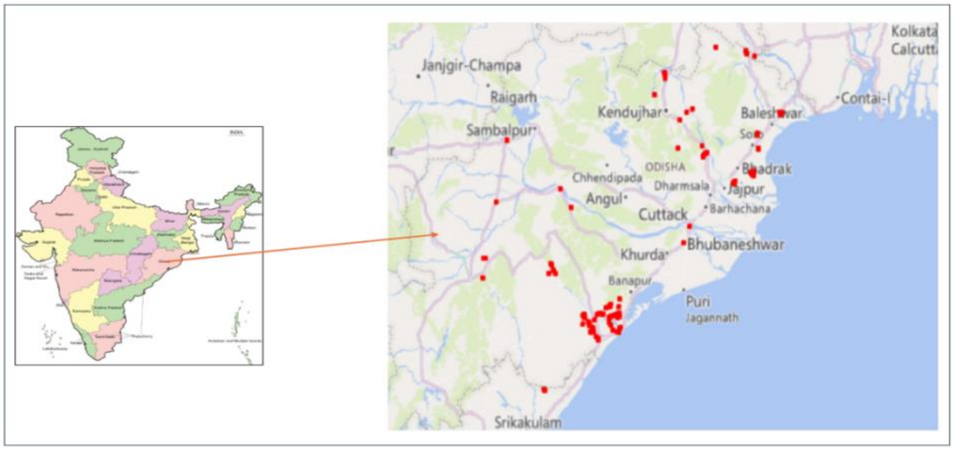


FIGURE 2. LOCATION OF THE RANDOMLY SELECTED FARMERS SURVEYED IN ODISHA

surveyed districts to ensure the suitability of the questionnaire in the local cultural context. Following successful pilot of the questionnaire, the main survey was conducted with the Kobo Toolbox application after ensuring the validity of the interview schedule. Farmers were informed about the project, and only those who provided consent by signing the consent form were interviewed. A day-long training session was conducted in Bhubaneswar to orient the enumerators on the study's objectives, survey methodology, and the purpose and meaning of the questions. The main survey was conducted between April and May 2024, and after meticulous review of the data (data cleaning with removal of outliers, missing information and validation), information from 194 sample aquaculture farmers was retained for analysis.

### *2.2 Ethical Approval*

On June 13, 2024, ethical approval for primary survey was obtained from the Centre for Media Studies-Institutional Review Board of the Government of India under the reference number CMS-IRB/Ag/2024/011 (IRB Number- IRB00006230). Informed consent was sought from each of the survey participants and the study considered information from those participants who gave their written consent to participate in the interview.

### *2.3 Empirical Model: Propensity Score Matching*

To measure the impact of programme participation by constructing randomized data in observational studies and when participants are not randomly assigned to treatment propensity score matching (PSM) is a suitable technique (Rosenbaum and Rubin, 1983; Caliendo and Kopeinig, 2008). Following Rosenbaum and Rubin (1985), Becerril and Abdulai (2010), Kassie et al. (2011) and Amankwah et al. (2018), the impact of farm management training programme on household wellbeing measured through annual fish farm income and monthly household expenditure on food is modelled as the following way:

Let Z={1,0} be the variable indicating aquaculture farm management training participation status, and Y1i represent the outcome when the farming household participates a training programme, and Y01 represent the outcome if the farm household do not participate. Thus, the potential outcome and training participation together are defined as:

$$\text{Potential outcome} = \begin{cases} Y_{1i}\ if\ Z\ =\ 1 \\ Y_{0i}\ if\ Z\ =\ 0 \end{cases}$$

And the observed household outcome is $Y_i\ = ZY_{1i}\ +\ (1\ -\ Z)Y_{0i}$ which equals $Y_{1i}$ if Z= 1, and $Y_{0i}$ otherwise.

Following Becker and Ichino (2002) and Abebaw and Haile (2013), the impact of training participation on income and consumption expenditure which is the average treatment effect on the treated (ATT) is defined as

$$ATT\ =\ E(Y_{1i}\ -\ Y_{0i}|\ Z = 1)\ =\ E(Y_{1i}|\ Z\ =\ 1)\ -\ E(Y_{0i}|Z\ = 1) \qquad (2)$$

For any aquaculture farm household, the difference between the potential outcomes $Y_{1i} – Y_{0i}$ is the causal effect of training on the household wellbeing. This assumes that we know the outcome of training participation but do not know the outcome had the aquaculture farmers were not the training participant. To form a counterfactual group, we impose the conditional independence assumption (CIA), also termed as 'un-confoundedness'. This assumption states that there exist a set of observables $X_i$ (such as, age, age squared, gender, marital status, education, smartphone, membership, aquaculture as primary occupation, distance to town, distance to all weather road, experience, household size, operational land holding) for which $Y_0$ is independent of the participation status $Z_i$ conditional on $X_i$ (Heckman *et al.,* 1998). This conditioning on Xi helps in creating randomized data of treatment assignment along with avoiding linear functional form assumption of the equations relating to $Y_{1i}$ and $Y_{0i}$ on $X_i$. Under such situation the ATT is redefined as

$$ATT\ =\ E(Y_{1i}\ -\ Y_{0i}|X)\ =\ E(Y_{1i}|Z\ = 1, X) - E(Y_{0i}|Z\ = 0, X) \qquad (3)$$

The idea behind PSM is to identify non-participant of training that are similar to participant based on observed covariates. Rosenbaum and Rubin (1983) suggested using covariate balancing score as single index variable *P(X)* that summarises the observed covariates and overcome the problem of dimensionality. The propensity score (*p*-score) of the *i*th household participating training is given as:

$$P\ (X)\ =\ Pr\ (z = 1) \mid X \qquad (4)$$

which the *p*-score is estimated by either a logit (default) or probit model that regress training participation dummy (participation= 1; otherwise=0) on observed socio-demographic characteristics of the farmers in Odisha. Thus if PSM is meant to identify non participant that are similar to participant of farm management training based on observed covariates, then it is also based on propensity scores, i,e., $Y_0 \perp D \mid P(X)$, where $\perp$ denotes independence; $Y_0$ is the outcome of non-participation which is independent of participation D given the propensity score. Conditional on *p*-score, the average treatment effect of training participation is presented as

$$ATT = E(Y_{1i} - Y_{0i} \mid P(X_i)) = E(Y_{1i} \mid P(X_i), Z = 1) - E(Y_{0i} \mid P(P(X_i), Z = 0) \quad (5)$$

During estimation, a common support assumption is imposed to rule out perfect predictability of $Z_i$ given $X_i$ $\{0 < P(Z= 1|X) <1\}$ which indicates the farm households an equal chance of being training participant or non-participant.

*2.4 Variable and Summary Statistics*

Table 1 presents the socio-demographic and outcome variables used in estimating the propensity score matching model. The outcome variable such as total annual household income presented in natural logarithmic value is equivalent to 5.08. The contribution of fish farm income to total household income for farm households irrespective of training participation status is 30.5 percent and monthly food consumption expenditure is INR 6859.28 (USD 82.24). With regards to the socio-demographic variables, the average age of the farm household head is almost 49 years, 65 percent are male headed and 95 percent of household head being married. Overall, the household head completes 9 years of schooling, 76 percent possess a smartphone that facilitates use of modern applications allowing access of new information related to training and other farm management related domains and only 8 percent of the farm household head is a member of the farmer business organization (FBOs). Other socio-demographic variables include aquaculture being primary occupation is considered by 26 percent of the total farm households, average distance of farms to the district town is 25.93 Km and distance to all-weather road is 4.33 Km. The average experience of fish farming in minor irrigation tanks is relatively less with 3.5 years only, while family size and aquaculture land of the surveyed farm household are 5 living members and 0.049 acre (4.92 decimal), respectively.

Table 2 presents the unconditional differences in well-being outcome variables between the training participants and non-participants, along with values of the covariates. Overall, 33.51 percent of the total farmers surveyed had previously participated in aquaculture-related farm management training. The logarithmic value of total annual household income is significantly higher for training participants than the non-participants. Specifically, the log of annual household income of training participants is about 0.30 more than that of non-participants. Without log transformation, the household income for training participants over non-participants are higher in the range of INR 32610.24 to INR 34317.97 (USD 391.01 to USD 411.48).

TABLE 1. DEFINITION AND SUMMARY STATISTICS OF SELECTED VARIABLES

| Variables | Definition | Type | Mean (Std. dev) |
|---|---|---|---|
| HHINCOME | Total household income of the aquaculture farmers | Natural logarithm | 5.08 (6.61) |
| FISHINCOME | Contribution of fish farm income to total household income (in %) | Continuous | 30.53 (21.70) |
| EXPFOOD[#] | Monthly household expenditure on food (INR) | Continuous | 6859.28 (2004.31) |
| AGE | Age of the household head (in completed years) | Continuous | 48.71 (12.22) |
| AGESQ | Squared term of age of the household head | Continuous | 2521.42 (1259.23) |
| GEND | Gender of the household head (Male= 1; 0= Otherwise) | Dummy | 0.65 (0.48) |
| MARRY | Marital status of the household head (1= married; 0= otherwise) | Dummy | 0.95 (0.22) |
| EDUC | Years of schooling of the household head (in completed years) | Continuous | 8.34 (5.36) |
| SMARTPH | Possession of a smartphone by the household head | Dummy | 0.76 (0.43) |
| MEMB | Whether the farmer is a member of fish producer group (1= yes; 0 otherwise) | Dummy | 0.08 (0.28) |
| PRIMAQUA | If aquaculture is the primary occupation of the household head (1= yes; 0= otherwise) | Dummy | 0.26 (0.44) |
| DISTTOWN | Distance of the farmer to the nearest district town (in Km) | Continuous | 25.93 (28.85) |
| DISTROAD | Distance of the farmer to the nearest all-weather road (in Km) | Continuous | 4.33 (3.76) |
| EXP | Number of years since first started fish farming | Continuous | 3.57 (4.78) |
| HHSIZ | Number of members living in the farm household | Continuous | 5.28 (2.32) |
| OPHOLD | Average size of land held by the farmer for aquaculture | Continuous | 4.92 (8.35) |

*Source: Field survey, 2024; [#]1 USD = INR 83.4 during completion of the survey*

TABLE 2. CHARACTERISTICS OF THE AQUACULTURE FARMERS BY TRAINING PARTICIPATION STATUS

| Variables | Training participation | | |
|---|---|---|---|
| | Participant (n= 65) | Non-participant (n= 129) | Difference |
| AGE | 46.57 | 49.79 | -3.22* |
| AGESQ | 2346.45 | 2609.59 | 263.14 |
| GEND | 0.80 | 0.58 | 0.22*** |
| MARRY | 0.94 | 0.95 | -0.01 |
| EDUC | 10.69 | 7.16 | 3.54*** |
| SMARTPH | 0.85 | 0.72 | 0.13* |
| MEMB | 0.11 | 0.07 | 0.04 |
| PRIMAQUA | 0.31 | 0.23 | 0.08 |
| DISTTOWN | 15.32 | 31.28 | -15.96*** |
| DISTROAD | 3.23 | 4.88 | -1.65*** |
| EXP | 4.05 | 3.33 | 0.71 |
| HHSIZ | 5.26 | 5.29 | -0.03 |
| OPHOLD | 6.68 | 4.04 | 2.63** |
| HHINCOME | 5.89 | 5.58 | 0.30*** |
| FISHINCOME | 46.23 | 22.61 | 23.62*** |
| EXPFOOD# | 7520.00 | 6526.36 | 993.64*** |

***Note:*** **, ** and *** indicate P-vale of <0.10, <0.05 and <0.01 of the variables; #1 USD = INR 83.4 during completion of the survey*

The difference in household income has a direct reflection on the well-being status of the farmers. Again, the contribution of fish farm income to total household income is significantly higher by 23.62 percentage points for training participants over non-participants. Furthermore, it is also observed from Table 2 that training participation, *ceteris paribus*, may significantly increase food consumption expenditure to the extent of approximately INR 994 against the non-participant counterpart. The mean difference test for various farm characteristics that may influence both the outcome variables of interest and training participation status indicates that non-adopters are likely to be constrained in terms of age, gender, and education of the household head, possession of a smartphone, distance to district town, distance to all-weather road, and operational land holding. Participants seem to be younger by 3.22 years and educated by 3.54 additional years of schooling. It is further observed that more male-headed household heads (22%) become training participants, and 13percent more participants possess a smartphone. The average distance of participants to the district town and the nearest all-weather road is less by almost 16 km and 1.65 km, respectively. Finally, as evident from the table, training participants have higher operational land holding by 2.63 decimals over non-participants.

III

## RESULTS AND DISCUSSION

### *3.1 Propensity Score Estimation*

The first stage of the analysis considers the estimation of the propensity scores using observed socio-demographic characteristics of the households surveyed. The socio-demographic characteristics may be classified into human capital, e.g., AGE, GEND, MARRY, HHSIZ, EXP; institutional capital, e.g., MEMB, PRIMAQUA, DISTTOWN, DISTROAD; physical asset, e.g., SMARTPH, OPHOLD (Mendola, 2007; Amankwah et al., 2018)

In our study, we have used the default logit model to estimate the propensity scores presented in Table 3. The significant determinants of aquaculture farm management-related training participation are AGE, GEND, EDUC, PRIMAQUA, and DISTTOWN. Relatively young farmers are more likely to participate in farm management-related training. The quadratic relation of age with training participation status points out that an additional increase in age brings down the participation rate. Furthermore, participation intensity is higher with male-headed household heads among the farms surveyed. Education of the household head is also associated positively and statistically significantly with training participation status. The farmers for whom aquaculture is a primary occupation are likely to have higher farm management-related training participation compared to the rest. A higher distance between the aquaculture farmers and the district town discourages the training participation, possibly due to constraints in the flow of information of training opportunities available for aquaculture farmers.

Post-estimation of parameters of conditioning variables, the propensity scores are predicted[2]. Among the training participants, the p-score lies between 0.0431 and 0.9148, with a mean of 0.4997, while that of non-participants, the p-scores lie between 0.0017 and 0.8068 with a mean of 0.2534. After imposing common support, the average p-score is 0.3305 and the matching process led to loss of only 2 observations. The distribution of the propensity scores of treated groups with their corresponding untreated groups and identification of the off-support groups is presented in Figure 3.

[2]Propensity scores are estimated in Stata 18 (SE version) using ‘psmatch2’ and other post-estimation command such as ‘psgraph’, ‘pstest, both’ etc. Bootstrap standard errors were estimated using bootstrap command with the default 50 replications.

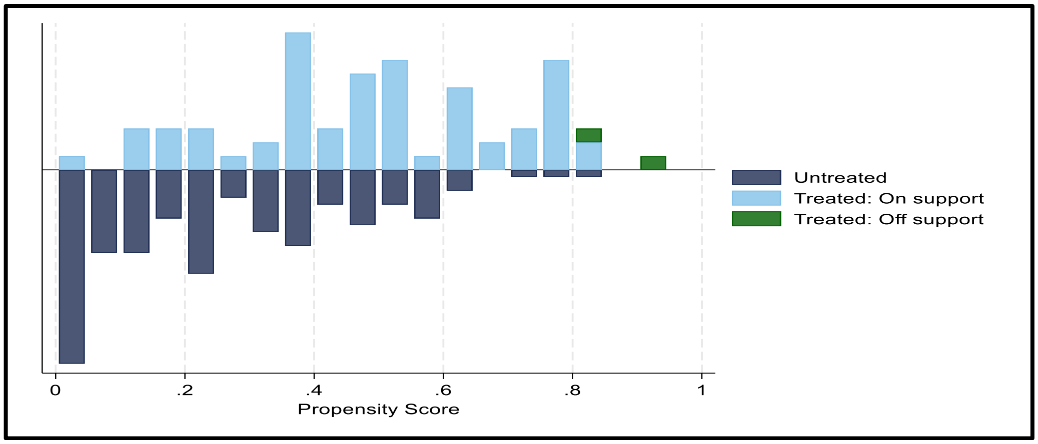


FIGURE 3. DISTRIBUTION OF PROPENSITY SCORES AND ESTIMATION OF COMMON SUPPORT FOR PROPENSITY SCORES

Note: "Treated: on support" indicates the observation of aquaculture farmers with access to information that have suitable comparison. "Treated: off support" indicates the observation of aquaculture farmers with information access that do not have suitable comparison

TABLE 3. LOGIT MODEL ESTIMATION OF FACTORS INFLUENCING TRAINING PARTICIPATION (TRAINING: 1= YES; 0= OTHERWISE)

| Variables | Coefficient | Std. error |
|---|---|---|
| AGE | -0.150** | 0.07 |
| AGESQ | 0.001** | 0.00 |
| GEND | 0.600** | 0.27 |
| MARRY | 0.295 | 0.51 |
| EDUC | 0.069*** | 0.02 |
| SMARTPH | 0.112 | 0.29 |
| MEMB | -0.004 | 0.46 |
| PRIMAQUA | 0.605** | 0.28 |
| DISTTOWN | -0.016*** | 0.01 |
| DISTROAD | -0.033 | 0.03 |
| EXP | 0.018 | 0.02 |
| HHSIZ | 0.017 | 0.05 |
| OPHOLD | -0.000 | 0.01 |
| Constant | 2.061 | 1.55 |
| LR Chi2 | 53.30*** | |
| Pseudo R2 | 0.2154 | |
| Log likelihood | -97.06 | |
| Number of observations | 194 | |

***Note:*** *Coefficient with ** and *** indicate P-vale of <0.05 and <0.01 of the variables*

*3.2 Covariate Balancing Test*

A major objective of propensity score estimation is to match the distribution of relevant covariates between the two groups of training participation: participants and non-participants. To ensure the elimination of the differences in the covariates of propensity scores estimation between training participants and non-participants, a covariate balancing test was performed. The covariate balancing test also informs that training participants and non-participants in the matched sample do not differ in terms of observable characteristics, except in participation status. Mean absolute standardized bias (MASB) was suggested for covariate balancing by Rosenbaum and Rubin (1985), which is estimated for each observable variable before and after matching, followed by the calculation of the average MASB. As a rule of thumb, the MASB after matching should not be more than 20percent, or else it indicates that the matching process has failed to create a counterfactual situation or led to bad matches. Additionally, in the covariate balancing test, Pseudo R2, likelihood ratio (LR) statistics, and their corresponding p-values are also estimated. The covariate balancing leads us to expect that the significant differences of training participation groups before matching are eliminated after matching by bringing the participants and non-participants to the same domain.

The estimated matching quality parameters (mean) are presented in Table 4. The MASB reduced from 29.9 percent in the unmatched sample to 7.9 to 8.9 percent in the matched sample for different matching algorithms and distributional assumptions. Overall, about 70-73 percent of the MASB of the conditioning variables was reduced through the matching process.

TABLE 4. PROPENSITY SCORE OF FISH FAMERS AND COVARIATE BALANCE BEFORE AND AFTER MATCHING

| Matching algorithms | Pseudo R2 unmatched | Pseudo R2 matched | LR Chi2 (P-value) unmatched | LR Chi2 (P-value) matched | Mean standardized bias before | Mean standardized bias after | Bias reduction (%) | Observations on support |
|---|---|---|---|---|---|---|---|---|
| KBM | 0.215 | 0.014 | 0.000 | 0.999 | 29.9 | 8.2 | 72.58 | 192 |
| NNM | 0.215 | 0.024 | 0.000 | 0.989 | 29.9 | 8.9 | 70.23 | 192 |
| RM | 0.215 | 0.015 | 0.000 | 0.999 | 29.9 | 7.9 | 73.58 | 192 |

*Note: KBM= Kernel based matching; NNM= Five nearest neighbour marching with replacement; RM= Radius matching with caliper 0.1.*

The Pseudo R2 reduced heavily from 21.5 percent in the unmatched data to almost 1-2 percent in the matched data, an implication of very little variation in trained aquaculture farmers is explained by the conditioning variables after matching. Furthermore, before matching the likelihood ratio test accepted the null hypothesis that covariates do not jointly explain the variation in training participation through a significant p-value. The joint significance test rejected the null hypothesis after matching. To sum it up, the estimated covariate balancing test results point out that after controlling for observable socio-demographic characteristics of the surveyed households, there is no difference between training participants and non-participants, except for their participation status.

*3.3 Average Treatment Effect on The Treated*

Three main propensity score matching algorithms commonly employed in the impact evaluation method using PSM are- kernel-based matching (KBM), nearest neighbor matching (NNM), and radius matching (RM). In the KBM, each treated observation is matched with all the control observations falling under common support. KBM is based on the weight that is inversely proportional to the distance between the propensity scores belonging to the treatment and control groups. We used the default bandwidth (0.06) of KBM in our analysis. The NNM approach matches the treatment and control groups in such a way that the matched pairs have the least possible differences in p-scores, with or without replacement. If matching is implemented with replacements, one control observation can be used to match more than one observation of the treatment group; otherwise, without replacements enables one-to-one matching. According to Caliendo and Kopeinig (2008), with and without replacement matching in NNM is a trade-off between bias and variance. Radius or caliper matching involves establishing a maximum distance (or caliper) around the propensity score of a treatment unit and matching it to all non-treated units falling under that radius. The magnitude of the average treatment effect on the treated is, though, different by use of different matching algorithms; the variations in qualitative results are less. We use the logarithm of total household income to normalize the heterogeneity and interpret the results in terms of percentage changes. Specifically, training participation has significant positive effects on total household income, share of fish income, and household food expenditure (Table 5). Based on KBM, single NNM, and RM show that training participation has a higher total log annual household income of 0.31 to 0.34 per trained aquaculture farmers compared to the controls. Again, after controlling for differences in observable socio-demographic variables, fish income contributes higher by almost 23 percentage points to the total household income of the farmers trained on better farm management. The estimated rise in monthly food consumption expenditure after training participation ranges from INR 643-721 (USD 7.71 -8.64) across matching estimators.

Agricultural (including allied sector) training programme facilitates knowledge and skill transfer on specific innovations or better practices with the anticipation of benefiting farmers (Stewart et al., 2016; Stewart et al., 2015, Wonde et al., 2022; Mahmud et al., 2012). However, as training costs substantial resources, the expected impacts remain very unclear most of the time due to the absence of rigorous assessment of impact (Spielman et al., 2010), which is very much akin to the condition in the Odisha state. With regular farm management-related training conducted for aquaculture farmers, yet without clear impact evidence to refer motivated to assess training impact using PSM in order to partially control selection bias.

TABLE 5. TREATMENT EFFECTS BASED ON PROPENSITY SCORE MATCHING

| Outcome variable | Matching algorithm | ATT | Bootstrap std. error | 95 conf. interval | |
|---|---|---|---|---|---|
| HHINCOME | KBM | 0.33*** | 0.07 | 0.18 | 0.48 |
| | NNM | 0.34*** | 0.08 | 0.18 | 0.48 |
| | RM | 0.31*** | 0.06 | 0.19 | 0.43 |
| FISHINCOME | KBM | 23.67*** | 3.72 | 16.38 | 30.95 |
| | NNM | 23.38*** | 4.24 | 15.07 | 31.70 |
| | RM | 23.07*** | 3.14 | 16.92 | 29.23 |
| EXPFOOD[#] | KBM | 642.74* | 375.50 | 39.23 | 1378.71 |
| | NNM | 721.27* | 373.25 | 10.29 | 1452.83 |
| | RM | 666.74* | 358.22 | 35.36 | 1368.84 |

** and *** significant at 10% and 1%, respectively; KBM= Kernel based matching; NNM= Five nearest neighbour marching with replacement; RM= Radius matching with caliper 0.1; [#]1 USD = INR 83.4 during completion of the survey*

Our study broadly reveals the impact of farm management-related training participation among the aquaculture farmers in the context of select districts in Odisha state of India, along with the socio-demographic factors influencing training participation status. Training to aquaculture farmers on farm management is time to time conducted in Odisha, primarily under central sector schemes such as Pradhan Mantri Matsya Sampada Yojana (PMMSY), along with other state-supported schemes, but there is very little evidence of such interventions impacting the well-being of the farmers through enhanced household income, fish income, and food consumption expenditure. We categorized the farmers in terms of exposure to training status and defined as a binary indicator variable to decipher its impact on household wellbeing, measured in terms of income and food consumption expenditure. The results of training participation impact on household income and consumption expenditure are positive and statistically significant (Table 5) and align well with some prior empirical works (Dompreh et al., 2024; Ragasa et al., 2022; Dickson et al., 2016). While estimating impact using PSM, the study did not address the hidden bias, such as the aquaculture farmers' motivation, prior knowledge and skills, and ability to manage aquaculture production in their farms. Few studies, while pointing out the actual impact of training intervention, also indicate other mediating factors such as the length of exposure to such interventions (Dompreh et al., 2024; Ragasa et al., 2022), water resources for aquaculture, experience with aquaculture production, etc (Filipski and Belton 2018). Training interventions not only foster skill building and impart new knowledge as mentioned before, but also build a favourable attitude (Argade et al., 2023), which not only raises productivity and production directly but sometimes influences profitability through farming cost reduction or control in fish mortality (Dickson et al., 2016; Ragasa et al., 2022). This suggests that measuring profitability or household income can be an effective instrument towards measuring the holistic impact of training interventions rather than the narrow measure of production and productivity alone.

The study has shown an increased contribution of fish farm income to total household income by 23 percentage points for training participants over non-participants. Positive impact on food consumption is also reported by other studies (Abebaw et al., 2010; Koomson et al., 2021; Dompreh et al., 2024). There is evidence of positive consumption impact at the household level after training participation, which is sometimes mediated by empowerment of women (Koomson et al., 2021) through literacy on financial and income-generating avenues. Dompreh et al. (2024) underscore the training effect towards fostering adoption of better management practices (BMPs), influencing improved dietary diversity among the trained farming households. Overall, the results of the PSM analysis guides us to postulate that training enhanced the technical skills of aquaculture farm management among the participants compared to their non-participant counterparts, which led to either increased productivity or reduced production costs, leading eventually to a rise in farming income and household consumption expenditure on daily food items.

## IV

## CONCLUSION

The present paper is about estimating the impact of training participation in the residential training programme among the aquaculture farmers in Odisha state of India. The study has used a matching framework by employing PSM econometric model to address selection bias based on observable covariates. The findings underscore the significant positive impact of training participation on annual household income, share of fish farm income to total household income and monthly household food expenditure. The training participants had 0.31-0.34 higher log of total household income ($p = 0.000$) vis-à-vis the counterfactual group across different matching algorithms used in the PSM technique. Regarding the share of fish farm income to total household income, training participants had a significantly higher share in the range of 23.07 to 23.67 percentage points ($p = 0.000$) compared to the non-participants. Furthermore, the monthly mean household food consumption expenditure is INR 6859.28 for an average of 5.28 household size, and training participants spend an average range of INR 643 to 721 ($p<0.10$) higher amount compared to the non-participants. The significant positive impact of the outcome variables signifies that training participation helped farmers get skilled in better farm management practices, which may have improved productivity or reduced production costs. Regular and close supervision and evaluation of training programmes are needed to ensure that the training given is standard, rightly targeted, and fulfils the actual objective of imparting training. Finally, further research is needed in the state to substantiate the findings of this study by addressing hidden selection bias. This would help to refine the existing training policies to optimal exploitation of the training programs' benefits, planned to be implemented in the future.

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REFERENCES

Abebaw, D., & Haile, M. G. (2013). The impact of cooperatives on agricultural technology adoption: Empirical evidence from Ethiopia. *Food Policy, 38*, 82–91. https://doi.org/10.1016/j.foodpol.2012.10.003

Abebaw, D., Fentie, Y., & Kassa, B. (2010). The impact of a food security program on household food consumption in Northwestern Ethiopia: A matching estimator approach. *Food Policy, 35*(4), 286–293. https://doi.org/10.1016/j.foodpol.2010.01.002

Amankwah, A., Quagrainie, K. K., & Preckel, P. V. (2018). Impact of aquaculture feed technology on fish income and poverty in Kenya. *Aquaculture Economics & Management, 22*(4), 410–430. https://doi.org/10.1080/13657305.2017.1413689

Ansah, Y. B., & Frimpong, E. A. (2015). Impact of the adoption of best management practices on social welfare: A case study of commercial floating feeds for pond culture of tilapia in Ghana. *Cogent Food & Agriculture, 1*(1), 1048579. https://doi.org/10.1080/23311932.2015.1048579

Argade, S., Pailan, G. H., Mahapatra, B. K., Dutta, S., Munilkumar, S., Dasgupta, S., & Xavier, K. M. (2023). Impact of skill development trainings on fish farmers' knowledge and attitude: A case study from Bihar, India. *Indian Journal of Fisheries, 70*(1), 1–17. https://doi.org/10.21077/ijf.2023.70.1.108797-17

Bairagya, I. (2021). Impact of formal vocational training on the earnings of self-employed individuals in rural India. *Journal of Business Venturing Insights, 16*, e00269. https://doi.org/10.1016/j.jbvi.2021.e00269

Baldwin, T. T., Ford, K. J., & Blume, B. D. (2009). Transfer of training: An updated review and agenda for future research. *International Review of Industrial and Organizational Psychology, 24*, 41–70. https://doi.org/10.1002/9780470745267.ch2

Becerril, J., & Abdulai, A. (2010). The impact of improved maize varieties on poverty in Mexico: A propensity score-matching approach. *World Development, 38*(7), 1024–1035. https://doi.org/10.1016/j.worlddev.2009.11.017

Becker, S. O., & Ichino, A. (2002). Estimation of average treatment effects based on propensity scores. *The Stata Journal, 2*(4), 358–377. https://doi.org/10.1177/1536867X0200200403

Belton, B., & Little, D. C. (2011). Immanent and interventionist inland Asian aquaculture development and its outcomes. *Development Policy Review, 29*(4), 459–484. https://doi.org/10.1111/j.1467-7679.2011.00542.x

Blume, B. D., Ford, J. K., Baldwin, T. T., & Huang, J. L. (2010). Transfer of training: A meta-analytic review. *Journal of Management, 36*(4), 1065–1105. https://doi.org/10.1177/0149206309352880

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys, 22*(1), 31–72. https://doi.org/10.1111/j.1467-6419.2007.00527.x

Dickson, M., Nasr-Allah, A., Kenawy, D., & Kruijssen, F. (2016). Increasing fish farm profitability through aquaculture best management practice training in Egypt. *Aquaculture, 465*, 172–178. https://doi.org/10.1016/j.aquaculture.2016.09.015

Dompreh, E. B., Rossignoli, C. M., Griffiths, D., Wang, Q., Htoo, K. K., Nway, H. M., & Gasparatos, A. (2024). Impact of adoption of better management practices and nutrition-sensitive training on productivity, livelihoods and food security of small-scale aquaculture producers in Myanmar. *Food Security, 16*(3), 757–780. https://doi.org/10.1007/s12571-023-01415-y

Dubey, S. K., Padiyar, A., Chadag, V. M., Shenoy, N., Gaikwad, A. B., Ratha, B. C., & Belton, B. (2024). Scaling community-based aquaculture for enhanced nutrition and women's empowerment: Lessons from Odisha, India. *Frontiers in Sustainable Food Systems, 8*, 1412686. https://doi.org/10.3389/fsufs.2024.1412686

Food and Agriculture Organization of the United Nations. (2016). *The state of world fisheries and aquaculture 2016: Contributing to food security and nutrition for all*. FAO. https://openknowledge.fao.org/handle/20.500.14283/i5555e

Filipski, M., & Belton, B. (2018). Give a man a fishpond: Modeling the impacts of aquaculture in the rural economy. *World Development, 110*, 205–223. https://doi.org/10.1016/j.worlddev.2018.05.023

Frimpong, E. A., Ansah, Y. B., Amisah, S., Adjei-Boateng, D., Agbo, N. W., & Egna, H. (2014). Effects of environmental best management practices on pond water quality and growth of Nile tilapia. *Sustainability, 6*(2), 652–675. https://doi.org/10.3390/su6020652

Heckman, J. J., Ichimura, H., & Todd, P. (1998). Matching as an econometric evaluation estimator. *Review of Economic Studies, 65*(2), 261–294.

Kassam, L., & Dorward, A. (2017). A comparative assessment of the poverty impacts of pond and cage aquaculture in Ghana. *Aquaculture, 470*, 110–122. https://doi.org/10.1016/j.aquaculture.2016.12.017

Kassie, M., Shiferaw, B., & Muricho, G. (2011). Agricultural technology, crop income, and poverty alleviation in Uganda. *World Development, 39*(10), 1784–1795. https://doi.org/10.1016/j.worlddev.2011.04.023

Koomson, I., Villano, R. A., & Hadley, D. (2021). Accelerating the impact of financial literacy training programmes on household consumption by empowering women. *Applied Economics, 53*(29), 3359–3376. https://doi.org/10.1080/00036846.2021.1878093

Ragasa, C., Amewu, S., Agyakwah, S. K., Mensah, E. T. D., & Asmah, R. (2022). Impact of aquaculture training on farmers' income: Cluster randomized controlled trial evidence in Ghana. *Agricultural Economics, 53*(S1), 5–20. https://doi.org/10.1111/agec.12754

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55. https://doi.org/10.1093/biomet/70.1.41

Stewart, R., Langer, L., Da Silva, N. R., & Muchiri, E. (2016). Effects of training, innovation and new technology on African smallholder farmers' economic outcomes and food security. *Campbell Systematic Reviews, 12*(1), 1–224. https://doi.org/10.4073/csr.2015.16

Toufique, K. A., & Belton, B. (2014). Is aquaculture pro-poor? Empirical evidence of impacts on fish consumption in Bangladesh. *World Development, 64*, 609–620. https://doi.org/10.1016/j.worlddev.2014.06.035

Wonde, K. M., Tsehay, A. S., & Lemma, S. E. (2022). Training at farmers' training centers and its impact on crop productivity and household income in Ethiopia: A propensity score matching analysis. *Heliyon, 8*(7), e09837. https://doi.org/10.1016/j.heliyon.2022.e09837

Yamane, T. (1967). *Statistics: An introductory analysis* (2nd ed.). Harper & Row.