Simulation-based Ex Ante Assessment of Sustainable Agricultural Technologies: An Application to Integrated Aquaculture-Agriculture in Bangladesh.

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1. Introduction

The evaluation of the potential for agricultural technologies to achieve the multiple objectives of sustainability – improved performance in economic, environmental and social dimensions – is at the forefront of various research initiatives, including ones promoting "sustainable intensification" (Montpellier Panel 2013) and "climate smart agriculture" (FAO 2014). Evaluating technologies for their performance in these multiple dimensions poses major conceptual, analytical and data challenges. In particular, it requires evaluating the farming system as an integrated unit, rather than individual production activities, and it requires linking the farming system to the other environmental or social outcomes that it may impact. Moreover, to appropriately assess these impacts, it is essential to represent the high degree of bio-physical and socio-economic heterogeneity that is typical of smallholder agricultural systems and the households using them.

The main goal of this report is to demonstrate and evaluate the usefulness of a simulation-based approach to *ex ante* multi-dimensional impact assessment that is designed to meet these analytical challenges, using the methods presented in Antle (2011) and Antle, Stoorvogel and Valdivia (2014). To implement these methods, we use the Tradeoff Analysis Model for Multi-Dimensional Impact Assessment (TOA-MD) that is available with documentation at tradeoffs.oregonstate.edu. The analysis utilizes data from a technology dissemination study of integrated agriculture-aquaculture (IAA) carried out by WorldFish in 2002-2005, together with a unique follow-up study of IAA carried out in 2012. IAA is defined as the use of management techniques that aim to sustainably increase productivity on small-scale farms by increasing bio-nutrient flows (BRF) among the components of the farming system. The goal of IAA is to improve smallholder farm households' incomes, as well as their nutrition through increased on-farm food availability and higher incomes.

In the simulation-based approach to *ex ante* impact assessment, simulation experiments are carried out to calculate the adoption rate of a new or alternative production technology and its economic, environmental and social impacts in a heterogeneous population of farms. The simulation-based approach can also be used to evaluate the impacts of exogenous changes in conditions, such as climate change. The simulation-based modeling framework is set up as follows: we parameterize a model of the form $\mu_k(p,h,a)$ where μ_k is a performance indicator related to an outcome k, p is a vector of exogenous variables (e.g., prices, farm characteristics), h indexes the type of production system, and a defines the behavior of the decision makers (e.g., farmers' risk attitudes or other behavioral factors). For example k could be the net returns of the farming system, and μ_k could be the population mean of k. We use the model to carry out simulation experiments, meaning we parameterize the model to represent a population of farms with given values of p and a, and we then evaluate the indicator μ_k for alternative productions systems – in this study, we compare systems associated with the management practices of farms before and after training in the use of IAA.

How then do we evaluate a model designed for *ex ante* impact assessment? Within this modeling framework, two types of *ex ante* assessment can be done: one is exploratory analysis, by which we mean an analysis of how a change in technology would affect the indicator μ_k under a set of plausible conditions defined by p and a; the other is prediction or extrapolation out of sample, by which we mean an analysis of technology adoption and its impacts in a population using predicted values of p and an a value for a assumed to represent behavior in the corresponding population. Exploratory analysis only requires that the model be valid and that a plausible range of p and a be specified, but prediction requires a valid model as well as the ability to predict p and know the correct value of a. The importance of exploratory *ex ante* assessment derives from the fact that in most cases the future values of p and a are not known, thus, even if we have a valid impact assessment model, we cannot predict actual impacts that will be observed in the future; but with a valid model we can correctly predict outcomes conditional on values for p and a, as well as a valid range of outcomes associated with a plausible range of values of p and a.

To illustrate the use of the model for exploratory analysis, we use the data from a training program by WorldFish in 2002-2005 to parameterize the model and then simulate adoption rates and impacts if IAA under conditions observed during that period. To demonstrate the use of the simulation-based approach for prediction or extrapolation out-of-sample, we use data collected during the training program in 2002-2005 to parameterize the model, and then we use observations of *p* from the follow-up survey done in 2012 to predict the adoption rate and impacts in 2012. To evaluate the possible effects of the behavioral parameter *a,* we simulate adoption rates and impact indicators over its entire range from zero to 100 percent which encompasses the profit maximization behavior as well as other behavior.

We implement the simulation-based approach by combining three elements: the "treatment-control" paradigm of randomized controlled trials; the statistical structure of the "selection-into-treatment" model used in the econometric program evaluation literature; and the behavioral assumption of economic rationality. To construct a relatively parsimonious parametric model, we assume that the outcome variables in the model follow bi-variate normal distributions or are mixtures of normal distributions. The analysis is comprised of the following components:

- The farming system currently in use (defined here as System 1) is characterized empirically with observational data, e.g., data derived from a statistically representative sample of the farm population of interest. In this study, small farms with a relatively low degree of bio-nutrient flows among the components of the farming system are defined as the population of interest. Before being trained in the use of IAA, they are considered to be using System 1 (i.e., not using IAA).
- The improved technology is defined as System 2. It is modeled by using the scientific understanding of the improved technology to estimate how its use would change the productivity and other attributes (e.g., types of crops grown, input use) of System 1. Estimates of the potential productivity effects are quantified using experimental, observational or modeled data. In this study, System 2 is the use of IAA. Based on research by WorldFish scientists showing that bio-resource flows are an indicator of IAA use, we estimate the effects of IAA training by estimating the effects that increases in bio-resource flows have on productivity and profitability.
- The data for Systems 1 and 2 are used to parameterize a simulation model based on the statistical structure of the "selection-into-treatment" model used in the econometric program evaluation literature (Heckman and Vytlacil

2007), where “treatment” is interpreted as adoption of System 2. Adoption is assumed to be motivated by the goal of increasing farm income, or by other factors that affect farmers’ willingness to adopt. The model used to implement the analysis is known as the Tradeoff Analysis Model for Multidimensional Impact Assessment (TOA-MD) (Antle 2011; Antle, Stoorvogel and Valdivia 2014). This model is publicly available in documented software (Antle and Valdivia 2011).

The implementation of the simulation-based approach must account for a basic fact: “treatment-control” data provide the basis to draw inferences about the average differences between farmers using Systems 1 and 2 (i.e., the “average treatment effect”), but such data by themselves cannot be used to determine adoption behavior, i.e., how many farmers in the population would want to change from System 1 to System 2. Consequently, data obtained from a randomized-controlled trial or similar observational data by themselves cannot be used to estimate impacts for the “treated” (i.e., adopters of System 2) or the “untreated” farms (i.e., farms that do not adopt System 2 and thus continue using System 1). To add this behavioral component to an *ex ante* analysis, the simulation-based approach presented in this report adds the behavioral assumption that farmers choose the system with the highest expected economic value. With this behavioral assumption, it is then possible to use the “treatment-control” data and the statistical structure of the “selection-into-treatment” model to simulate an adoption rate as well as the resulting impact indicators for adopters (“treatment effect on the treated”), non-adopters (“treatment effect on the untreated”), as well as the effects on the entire population.

Once the simulation model is parameterized, we use the observations from the training period (2002-2005) and the follow-up data from 2012 to investigate a number of hypotheses related to IAA adoption and impacts. These hypotheses include:

H1*: Recommended IAA practices are economically feasible for more than 50 percent of the target population of small farms for which pond aquaculture is technically feasible.*

H2: *After training, some farmers do not continue to use IAA practices, so the rate of adoption is less than 100%. Incomplete adoption of IAA technologies is explained by: (a) differences in average productivity and/or cost of production among farms; (b) variability in productivity and/or cost of production.*

H3: *Adopters of IAA practices have lower poverty and better nutrition than non-adopters.*

H4*: (a) Adoption and (b) impacts of IAA practices are the same for small and large farms.*

At the outset we emphasize two key points about this analysis. First, in this study we use data collected for the original WorldFish evaluation of its IAA training program, for which WorldFish randomly selected four villages that were deemed to be representative of the target population of farms for dissemination of IAA practices. Our goal in this study is to use these data to demonstrate and test the simulation-based approach to ex ante impact assessment. This study is not designed to address whether this sample of farms is representative of the larger population, nor do we intend to evaluate whether the effects of IAA observed in these villages can be extrapolated to other regions, or whether changes observed in the wider population could be attributed to the activities of WorldFish.

A second important point concerns our use of the term “adoption.” In this study we will be examining the effect of an IAA training program on the use of practices associated with IAA. Thus, we define “adoption of IAA” to mean that a farmer uses some combination of the management techniques provided in the IAA training program to increase the degree of integration among the aquaculture, crop and livestock activities on the farm, as described in section 2. However, it is difficult to observe all of the management practices that farmers actually use, so we employ a more readily observable indicator of integration to evaluate IAA adoption, defined as the number of bio-resource flows (BRF). Thus, in this study, “adoption” does not mean the dichotomous choice between use and non-use of a single factor, such as an improved crop variety, but rather an increase in integration and thus an increase the number of BRF on the farm. Accordingly, the target population for the training program is farms with a relatively low degree of integration before training; farms that had a high level of integration before training are not expected to benefit much from the training, and the data presented in this study show that this is indeed the case.

This report is structured as follows. The second section describes the research underlying the development of Integrated Agriculture-Aquaculture (IAA) technology and the implications for quantifying the productivity effects of IAA using bio-resource flows (BRF). It also describes the project carried out by WorldFish to disseminate the technology and the training program that is the source of some of the data used in this study. The third section provides an overview of the simulation-based integrated assessment framework and how it is implemented using the Tradeoff Analysis Model for Multi-Dimensional Impact Assessment (TOA-MD). The fourth section: describes the data used for implementing the simulation-based model and for evaluating its predictions; presents analysis of the data using conventional statistical and econometric methods; and outlines a number of methodological questions that are relevant to the evaluation of the simulation model. The fifth section presents the results of the simulation-based analysis, and evaluates the simulation model predictions relative to the observations made in the 2012 survey. The final section summarizes our findings.

2. Development and Dissemination of IAA in Bangladesh

WorldFish has a long history of involvement in the development and adaptation of appropriate aquaculture technologies and management practices for smallholder farms in various countries, including Bangladesh. With the objective of generating an appropriate and sustainable low cost aquaculture technology for smallholder rural farmers, WorldFish started IAA based aquaculture research in Bangladesh in 1990s. The basic principle of IAA is to enhance on-farm resource use efficiency and productivity via the integration of resource flows between terrestrial and aquatic sub-systems. IAA moves from a fishpond focus to a whole farm perspective utilizing ponds and paddy fields by optimizing management of on-farm resources (Figure 1). IAA is thus a knowledge-intensive holistic approach that integrates numerous component technologies within systems management.

Building on the technology base from projects in the 1990s, the Development of Sustainable Aquaculture Project (DSAP) ran from 2001 through 2005 and was implemented in 34 of the 64 districts in Bangladesh aimed at improving resource use efficiency and sustainably increasing productivity at the farm level through IAA. The various alternatives for IAA can be combined selectively depending on farmer conditions. The project provided multiple training opportunities to over 63,000 farm households and reached many more through other communication strategies. Farmers were exposed to a basket of 19 technologies and management practices.

Expected outcomes from the DSAP project were that improved productivity would result in increased farm income and farm household food consumption, although the economic benefits will depend on how IAA practices affect labor and other costs that are required to achieve these gains in productivity. Project monitoring reports document widespread adoption of many of the component technologies and studies have examined the additional profitability achieved (Jahan et al, 2008; Jahan et al, 2010; Jahan & Pemsl, 2011). Widely adopted technologies include IAA based carp polyculture, carp-shrimp polyculture, and nursery management practices in ponds and rice fields (DSAP 2005). Dey (2000) shows the income elasticity of demand for fish by different fish types range from 0.15 – 1.76 whereas the income elasticity for other foods is near zero. Thus an increase in income could be expected to influence fish consumption whether purchased or home produced, and increased availability through home production is expected to increase fish consumption as well. Jahan and Pemsl (2011) showed that IAA adoption led to higher food consumption as a result of increased farm productivity and income. Among the food items, the per capita fish consumption of the project households increased from 47 g/day/person to 56 g/day/person from 2003/04 to 2005/06, exceeding the average per capita national consumption of 32 g/day/person (Bangladesh Economic Review, 2005).

2.1 The DSAP approach to farmer participatory research and extension

WorldFish applied a new Farmer Participatory Research approach in DSAP in which the potential for farmers to add an additional enterprise to their farms through fish farming was assessed. This approach, termed RESTORE (Research Tools for Natural Resource Management, Monitoring and Evaluation), is a combination of farmer-participatory field procedures and an analytical database (Lightfoot et al. 1994; 2000). The research procedures that comprise RESTORE are designed primarily for use by farming systems researchers, extension specialists and development field workers. It is focused on farmer participatory research at the farm and village levels. The objective is to assist farmers in identifying ways in which they can incorporate environmentally sound resource management strategies into their farming systems. RESTORE involves a four-step process of learning, planning, experimentation and evaluation.

The RESTORE approach encourages the use of integrated agriculture-aquaculture (IAA), in which existing resources (in the form of organic wastes and byproducts) from on and around the farm are utilized as nutrient inputs to the pond and to other enterprises; reducing the need for purchase of off-farm inputs such as inorganic fertilizers, and thereby reducing production costs, maximizing the use of on-farm resources, and leading to improved environmental sustainability (Lightfoot et al. 1993, Lightfoot and Noble 2001). This approach was implemented by Research Extension Teams (RETs) under the farmer-scientist research partnership concept. The relationships established with farming communities under the project also facilitated the collection of longer-term monitoring data on technology adoption and impact which was collected using the RESTORE methodology (Lightfoot et al. 2000).

An important aspect of the extension approach adopted by DSAP was the introduction of long-term training and extension support to farmers. Earlier research indicated that short-term training was insufficient to enable farmers to successfully and independently practice IAA since it requires a detailed understanding of particular aspects of the farming system (Alam et al. 2004). Thus long-term training and close extension support were provided to the project farmers. These farmers received three training sessions during the first year, two during the second year, and a single period of follow-up training in the final year. Formal training was complemented by regular informal training sessions, such as group meetings at the pond or plot site using the RESTORE based participatory learning approach and annual participatory evaluation sessions. Under the approach community members and field staff learn together while going through the process. They, for example, jointly identify fish culture management issues, initiate actions to address those issues, monitor the results of the actions and the process used, and then reflect upon the results to determine future actions.

2.2 Characterization of IAA adoption using bio-resource flows

As illustrated in Figure 1, a key feature of IAA systems is the use of bio-resource flows among the components of the farming (Little and Muir, 1987; Ruddle and Zhong, 1988; Edwards, 1993; Lightfoot et al., 1993; Dalsgaard and Prein, 1999; Prein, 2002). Integrated farming that includes aquaculture can be broadly defined as the concurrent or sequential linkages between two or more farming activities, of which at least one is aquaculture (Edwards, 1993). In an IAA system the pond may provide additional benefits such as water storage capacity and improved soil fertility in addition to the returns from fish culture. Fish in ponds can be used to process many forms of agricultural by-products, including livestock and poultry manure and convert this manure into high-grade fish protein. Ponds and crops can be integrated using crops and crop residues as feeds and fertilizers for fish and pond sediments and water can be used as crop fertilizers and irrigation water, respectively (Ruddle et al. 1988; Little and Muir, 1987). The recycling of biological resources, wastes and by-products can improve farm natural resources and incomes.

Bio-resource flows (BRF) can be expressed in several "currencies" including biomass, nitrogen, energy, and monetary value. A practical method of approximating the magnitude of nutrients and biomass moving between sub-systems that has been used by WorldFish in its research and training is the number of distinct BRF. The number of BRF has been found to be the most useful way to discuss re-cycling of nutrients with farmers (Lightfoot et al., 1993a; Dalsgaard and Prein, 1999; Prein, 2002). In earlier research, some studies defined IAA in terms of farms having more than a certain level of BRF. For example, in a study in Malawi where many farms did not practice IAA, the use of 3 or more BRF was considered an indication of IAA adoption (Dey et al., 2006). However, this approach of using an absolute threshold is not appropriate in the context of Bangladesh where most farms practiced some degree of integration with BRF management before training, and the goal of the training was to increase the degree of integration. As we shall see below, in the DSAP study an average of about 5 BRFs were being used among the target group farmers even before training. Therefore, in this study we define the successful adoption of IAA in terms of the change in BRF: IAA training should increase the number of BRFs, and should increase them more for farms with relatively low BRFs than those with high numbers of BRFs. Farms that already have high levels of BRF are not considered to be the target population and are not expected to change practices much in response to the training even if they are among the trained group. In section 4 below we present data that confirm that training has these effects on the use of BRF, and thus validate its use as an indicator of the use of the practices being promulgated through training. Another important aspect of IAA is increasing the use of organic inputs along with the increase in integration. We also investigate the role of increased organic matter in the adoption of IAA in the analysis below.

3. Simulation-Based *Ex ante* Impact Assessment: Conceptual Approach and Implementation

Ex post impact assessment uses observations of farmers that have already adopted a technology to measure adoption rates and quantify the technology's impacts. In *ex post* assessment, a key methodological challenge is to define and measure the counterfactual – what would have happened if adopting farmers had not adopted the technology? Using the "system" terminology introduced in the introduction, we can say that in *ex post* assessment the analyst observes outcomes associated with farmers using System 2 (in this case, using IAA practices to increase integration), and then attempts to infer the outcomes that would have been observed if adopting farmers had been using System 1 (a less-integrated system not using IAA practices). The observed outcomes are compared to counterfactual outcomes to evaluate the impact of the technology.

In contrast, *ex ante* assessment is forward-looking, and strives to evaluate what could happen under a specified set of conditions when a new technology is introduced. Thus, in *ex ante* assessment the analyst observes outcomes associated with the use of System 1 (a system with low integration), and uses data and models to quantify the outcomes that would be associated with the use of System 2 (a system using IAA practices to increase integration) under a specified set of conditions. When a simulation model is used to compute these outcomes for System 2, we say we are using simulation experiments. In our analysis of IAA that is presented below, we define System 1 as the use of a farming system with a low degree of integration, and System 2 as one with a high degree of integration, i.e. the use of some combination of practices associated with IAA.

In this analysis, System 1 earns an expected value of v(*p*,1) and System 2 earns an expected value of v(*p*,2), where *p* is a vector of exogenous variables such as prices and farm characteristics. If the choice between systems can be made each production period, then *v* can be interpreted as a single-period return; or if the choice is made for a multi-period planning horizon, *v* can be a present value or an annuitized value over this period that includes fixed costs of changing systems. Systems are ordered according to the variable $\omega = v(p,1) - v(p,2)$, such that individuals with $\omega < a$ choose System 2 and otherwise choose System 1. The parameter *a* is defined as the *adoption threshold*. Note that if $a = 0$, decision makers choose the system with the highest expected value. A non-zero value of *a* can be used to represent a situation where some other factor influences adoption. For example, a value of $a < 0$ can represent the effect of a tax on System 2, or can represent the increase in the risk premium associated with System 2 if farmers are risk averse and System 2 is riskier than System 1; a value of $a > 0$ can represent a subsidy for System 2 or a lower degree of riskiness.

Due to heterogeneity in the farm population, ω is a random variable that follows the distribution $\varphi(\omega| p)$. It is important to be clear that this distribution represents the heterogeneous expectations of returns among farmers in the population, and does not represent the random distribution of returns faced by an individual farmer. The adoption rate of System 2 is defined as the proportion of farms using System 2, given by the cumulative distribution function $r(p,2,a) \equiv \int_{-\infty}^{a} \varphi(\omega| p)\, d\omega$. Note that $r(p,2,a)$ is analogous to the selection probability in a sample selection model.

In addition to estimating an adoption rate, the goal of the impact assessment is to evaluate the effects of adoption on an outcome *k* that is associated with the choice of system. For example, *k* could be farm income, or per capita household income, or nutritional status of household members. Because this variable *k* is also affected by the choice of system, it is jointly distributed in the population with ω according to the density $\phi(\omega,k|p,h)$, where $h = 1,2$ indexes the system. The ultimate goal of an impact assessment is to evaluate impact indicators related to the outcome variable *k*. In the introduction of this report, we defined such an impact indicator as

$\mu_k(p,h,a)$. For example, most *ex post* assessments use mean outcomes as impact indicators, and likewise in an *ex ante* assessment $\mu_k(p,h,a)$ can be a mean outcome and can be derived from knowledge of $\varphi(\omega| \text{p})$ and $\phi(\omega,k|p,h)$ as shown by Antle (2011). In this framework it is also possible to use other functions of *k*, such as the proportion of the population with an outcome above or below a threshold value. An important example of a threshold indicators is a headcount poverty rate. In this case *k* is per capita income, and the indicator is defined as the proportion of individuals or households with per capita income less than the poverty line.

3.1 The TOA-MD Model

The simulation-based *ex ante* assessment approach has been implemented as the Tradeoff Analysis Model for Multi-dimensional Impact Assessment (TOA-MD); see Antle (2011), Antle and Valdivia (2011) and Antle, Stoorvogel and Valdivia (2014) for technical details. The model is available with documentation at *tradeoffs.oregonstate.edu*. The TOA-MD model is based on the same logical structure as the “generalized Roy model” found in the econometrics literature (Heckman and Vytlacil 2007). As discussed in the previous section, the model is composed of the distribution of the variable ω (equal to the difference in the expected value of Systems 1 and 2) and the distributions of one or more outcome variables *k*. In the TOA-MD implementation, a population can be stratified into sub-groups or strata, each with its own outcome distributions. One of the key statistical assumptions of this model as it is implemented here is that these distributions are assumed to be Gaussian for each stratum. In cases where observed distributions are non-normal for a population, the analyst can stratify the population into approximately normal sub-populations (strata), implement the analysis for each stratum, and then aggregate the strata to approximate the non-normal distribution for the whole population as a mixture of normally distributed strata. As described in the previous section, the TOA-MD model uses the properties of outcome distributions to calculate (simulate) an adoption rate, mean outcomes for adopters and non-adopters for a specified value of an adoption threshold. By simulating adoption rates over the entire range of possible values of the adoption threshold *a*, all possible values of the adoption rate (from zero to 100 percent) and corresponding impact indicators can be obtained.

We use the following definitions:

v(*p*,1) ≡ expected net returns to System 1, normally distributed in the population of farms with mean $\mu_v(p,1)$ and variance $\boldsymbol{\sigma_v^2}(p,1)$

v(*p*,2) ≡ expected net returns to System 2, normally distributed in the population of farms with mean $\mu_v(p,2)$ and variance $\boldsymbol{\sigma_v^2}(p,2)$

h ≡ system index = 1,2

k(*p*,*h*) ≡ an outcome variable associated with system *h* which can be v or some other outcome of interest (e.g., per capita income, nutritional or other outcomes)

ω ≡ v(*p*,1) – v(*p*,2) = opportunity cost of changing from System 1 to System 2; defined over the interval (-∞,+∞)

p ≡ prices and other exogenous variables that characterize the farming system

a ≡ adoption threshold; System 1 is used if $\omega < a$ and System 2 is used otherwise; defined over the interval (-∞,+∞)

The distribution φ(ω| *p*) is normally distributed with mean μ_ω and variance $\boldsymbol{\sigma_\omega^2}$, where

$\mu_\omega(p)= \mu_v(p,1) - \mu_v(p,2)$

$\sigma_\omega^2(p)= \sigma_v^2(p,1) + \sigma_v^2(p,2) - 2\rho_v\sigma_v(p,1)\sigma_v(p,2)$.

ρ_v ≡ correlation between v(*p*,1) and v(*p*,2)

The distribution ϕ(ω,*k* | *p*,*h*) is a bi-variate normal distribution with parameters:

$\mu_k(p,h)$ ≡ mean of *k*(*p*,*h*)

$\boldsymbol{\sigma_k^2}(p,h)$ ≡ variance of *k*(*p*,*h*)

$\theta_k(p,h)$ ≡ correlation between outcome *k*(*p*,*h*) and ω.

The TOA-MD model uses the following equations to compute the adoption rate and mean impact indicators for each value of the adoption threshold *a*:

- The adoption rate:

(1) $r(p,2,a) = \int_{-\infty}^{\boldsymbol{a}} \varphi(\omega|\, p)\, d\omega$

Using the above, the following parameters can be computed for a given adoption threshold *a*:

- The mean of *k* for system *h:*

(2) $\mu_k(p,h,a) = \mu_k(p,h) - (-1)^h\ \sigma_k(p,h)\theta_k(p,h)\lambda(p,h,a)$,

where

$\lambda(p,h,a) = \varphi(a|\ p)/r(p,h,a) \equiv$ inverse Mill's ratio for system *h*

- The counterfactual means of outcome *k* for systems 1 and 2:

(3) $\widetilde{\mu_k}(p,1,a) = \mu_k(p,2) - \sigma_k(p,2)\theta_k(p,2)\lambda(p,1,a)$.

(4) $\widetilde{\mu_k}(p,2,a) = \mu_k(p,1) + \sigma_k(p,1)\theta_k(p,1)\lambda(p,2,a)$.

- Average treatment effect (ATE) for outcome *k*:

(5) $ATE_k(p) = \mu_k(p,2) - \mu_k(p,1)$

- Average treatment effects on the treated (TT) and untreated (TU) for outcome *k*:

(6) $ATT_k(p,a) = \mu_k(p,2,a) - \widetilde{\mu_k}(p,2,a)$

(7) $ATU_k(p,a) = \widetilde{\mu_k}(p,1,a) - \mu_k(p,1,a)$

As noted above, in addition to these mean indicators, the TOA-MD also computes threshold indicators and their counterfactuals (i.e., the proportion of an outcome *k* that exceeds a given threshold value).

Figure 2 illustrates the analysis of mean impact indicators, where the right-hand quadrant shows ellipsoids of equal density for $\phi(\omega,k|p,h)$, $h = 1,2$, and the left-hand quadrant shows the corresponding relationships between the adoption rate (or selection probability) and the mean impact indicators that are obtained as the adoption threshold is varied over its entire range of $(-\infty,+\infty)$ and thus the adoption rate varies over its range of (0,1). In this figure, $\mu_k(p,h,0)$ represents the mean for the sub-population that has chosen to use System *h*, given *p* and $a = 0$, and $\mu_k(p,h)$ represents the mean that is obtained if the entire population is using system *h.* Also, we define $\widetilde{\mu_k}(p,2,0)$ as the counterfactual mean obtained from System 1 for the adopters of System 2.

In a conventional *ex post* analysis of selection behavior, the selection variable ω would be treated as a latent variable, and observations of non-adoption (choice of System 1) and adoption (choice of System 2) would be used to estimate the distribution $\varphi(\omega| p)$. Figure 2 can be used to illustrate the various results in the econometric policy evaluation literature. For example, the average outcome observed for adopters (users of System 2) would be an estimate of $\mu_k(p,2,0)$, and observations of non-adopters (users of System 1) would provide an estimate of $\mu_k(p,1,0)$. Comparison of these two means would result in a biased estimate of the "average treatment effect on the treated" defined as ATT = $\mu_k(p,2,0) - \widetilde{\mu_k}(p,2,0)$. The bias that results from using $\mu_k(p,1,0)$ rather than $\widetilde{\mu_k}(p,2,0)$ as the adopter counterfactual is due to the fact that ω and k are correlated (assumed to be positively correlated in Figure 2, as shown by the positive slope of the axis of the ellipsoid representing System 2 in Figure 2). If selection were random, ω and k would be uncorrelated, the axes of the ellipsoids would be horizontal so that $\mu_k(p,1,0)$ would equal $\widetilde{\mu_k}(p,2,0)$, and there would be no selection bias. In that case it would also be true that all the treatment effects would be equal, i.e., ATT = ATT = ATU.

In *ex ante* analysis a random sample of the population provides unbiased estimates of the parameters of the distributions of $\varphi(\omega| \mathrm{p})$ and $\phi(\omega,k|p,h)$ that are related to System 1, such as the means, variances and correlations between v and k. However, the corresponding parameters for System 2 are not observable, and have to be estimated using other information, typically from experimental data (e.g., on-farm trials of new crops or management practices, or randomized controlled trials such as the IAA training program used in this study). It is also possible to use results from other models, such as crop or livestock growth models, to estimate effects of a new technology such as an improved crop or animal variety. Once $\varphi(\omega| \mathrm{p})$ and $\phi(\omega,k|p,h)$ are parameterized, it is then possible to construct the relationships shown in the left-hand side of Figure 2, and thus to calculate all of the impact indicators shown in the figure as well as all of the conventional treatment effects.

3.2. Implementing the TOA-MD Model with Before-After and Control-Treatment Data

As we discuss in section 4 below, data are available from an IAA training program carried out in 2002-2005 in two forms: before and after the training of a group of farmers; and for a trained group (also called the treatment group) and a control group. Under appropriate conditions, both of these types of data can be used to parameterize the TOA-MD model as presented above. The key requirement is that the data should provide unbiased estimates of the parameters of the distributions $\varphi(\omega| p)$ and $\phi(\omega,k|p,h)$ illustrated in Figure 2.

Before-after data could provide such estimates under the assumption that conditions do not change over time, or by using appropriate statistical methods to control for changes in conditions. One advantage of before-after data is that if they represent the same sample of farms over time (i.e., panel data), they provide an estimate of the between-system correlations ρ_v and θ_k .Control-treatment data could provide unbiased parameter estimates as well, if the control group is good match for treatment group. However, control-treatment data do not provide estimates of the between-system correlations unless matching methods are used to match treated individuals with corresponding control observations.

3.3 Implementing the TOA-MD Model as a Random Coefficient Model

For many *ex ante* studies, as well as for extrapolations, before-after or control-treatment observations of farms are not possible. In these cases, the analyst needs to construct a representation of System 2, typically starting with observational data for System 1. We illustrate now how the TOA-MD model can be implemented in this way using the concept of a random coefficient model. For notational convenience, let v_h represent v(p,*h*). Observe that it is always possible to express the ratio of two strictly positive random variables, such as the ratio v_2/v_1, in the form $\beta = v_2/v_1 = \mu_\beta + \sigma_\beta \eta$,

where η is assumed to be a random variable with mean zero and unit variance. Now let $\sigma_{\eta 1} = E(\eta v_1)$, and define $\varepsilon = \sigma_\beta \eta v_1 - \sigma_\beta \sigma_{\eta 1}$, implying $E(\varepsilon) = 0$. It follows that,

(8) $v_2 = \beta\, v_1 = \mu_\beta\, v_1 + \sigma_\beta \eta v_1 = \sigma_\beta \sigma_{\eta 1} + \mu_\beta\, v_1 + \varepsilon$.

Also defining $\sigma_{\varepsilon 1} = E(\varepsilon v_1)$, $E(v_1) = \mu_1$, $E(v_2) = \mu_2$, and defining the standard deviation of v_h as σ_h we have:

(9) $\mu_2 = \sigma_\beta \sigma_{\eta 1} + \mu_\beta \mu_1$

(10) $\sigma_2^2 = \mu_\beta^2 \sigma_1^2 + \sigma_\beta\,(\sigma_1^2 + \mu_1^2\,) + \mu_\beta \sigma_{\varepsilon 1}$

(11) $\rho_v = (\mu_\beta^2 \sigma_1^2 + \sigma_{\varepsilon 1})^{1/2} / \sigma_1 \sigma_2$.

Thus, given observations of farmers using System 1 so that we can estimate μ_1 and σ_1, and given data sufficient to estimate μ_β, σ_β, $\sigma_{\eta 1}$ and $\sigma_{\varepsilon 1}$, it is possible to estimate all of the parameters of the TOA-MD model. In many cases it will be difficult to estimate the covariances $\sigma_{\eta 1}$ and $\sigma_{\varepsilon 1}$ which measure the association between productivity or profitability levels of System 1 and the relative change from System 1 to System 2. Logic suggests that in many situations, the proportional effect of a new technology on productivity is independent of the level of productivity of the existing technology, implying that $\sigma_{\eta 1}$ is near zero (implying $\sigma_{\varepsilon 1}$ is also zero). We make that assumption below in section 4 where we discuss how an econometric model can be used to estimate these parameters.

3.4 Notable Features of the TOA-MD Model

The threshold adoption model that is the foundation of the TOA-MD model shows that the adoption rate is a function of the mean and variance of ω which are in turn functions of the parameters of the distributions of expected values of the two systems, v(p,1) and v(p,2). The variance of ω is determined by the variances and covariance of v(p,1) and v(p,2), demonstrating that the heterogeneity of returns, as well as their covariance, play important roles in determining adoption rates. In the analysis of IAA below, we explore these effects.

As these formulas show, another important feature of the TOA-MD model is its parsimony, derived from the use of the bivariate normal distribution that has a small number of parameters that are easily interpreted. The adoption rate is predicted using the means and variances of the net returns for each system and their correlation, a total of 5 fundamental parameters. For construction of the mean and variance of returns to each system, the analyst may choose to disaggregate the farming system into sub-systems, each with their own mean, variance and covariances. For each outcome variable there are up to seven additional parameters, a mean and a variance for each system, and three correlations. Thus, with farm net returns plus *n* other outcomes, the total number of parameters is equal to 5 + 7*n*. This relatively small number of parameters makes this model easy to interpret and easy to use for *ex ante* analysis or extrapolation, and also easy to use for sensitivity analysis to parameter values. This parsimony may come at the cost of bias from over-simplification. In particular, below we will investigate the accuracy of estimates of poverty rates when the distribution of per capita income is assumed to be Gaussian.

Another important and challenging issue in assessing technology adoption is how to define the "technology" that is being adopted. For example, in considering the adoption of a new crop variety, is "adoption" defined in terms of only the type of variety used, or also in terms of associated inputs such as fertilizer, pesticides, labor, as well as changes in resources allocated to other production activities? In the case of IAA studied here, the technology is a package of practices used to increase the integration across the crop, livestock and aquaculture components of the system. An important feature of the TOA-MD model is that it allows a system to be represented realistically as a set of production activities and associated management practices, but all farms need not be using those components in precisely the same manner (some farms may use more fertilizer than others, for example). System 1 and System 2 are distinguished by the fact that, if used by a given farm population, they would generate different distributions of returns and other environmental or social outcomes.

Finally, it is important to note that in implementing the TOA-MD model, we are using the distribution of *observed* returns to estimate parameters of the distribution of *expected* returns. Of course, the two distributions are not generally or necessarily equal, but under some plausible assumptions the two distributions are likely to be similar, and this is a maintained hypothesis underlying the implementation of the model.

4. Data, Target Population, and Parameter Estimation

The TOA-MD modeling approach involves a series of steps to design and implement an analysis. The first steps are to define the relevant population, characterize the main components of the farming system, and the outcomes and indicators to be used. Next come the identification of data, use of the data to parameterize the model, and use of the model to simulate the adoption rate and associated impacts. As discussed in Section 2, the population of farms was identified as small farms with a low degree of integration, and the main components of the farming system are identified as cereal crops (mainly rice), other crops, livestock and aquaculture.

4.1 Data

As described in section 2, the data used in this study come from surveys conducted during the DSAP project in 2002/03-2005/06 and a follow-up survey designed and implemented as part of the present study in 2012-2013. Henceforth we refer to these years as 2002, 2005 and 2012 for simplicity. The DSAP monitoring and evaluation unit operating through the research component RESTORE gathered the earlier data. One village was randomly selected from four districts that were considered to be representative of the larger population of interest (Mymensingh, Comilla, Magura and Bogra), and 260 farms were selected from these four villages for the training program that started in 2002 (Figure 3). Although the DSAP was completed in July 2005, program support was extended for a further year among these project farmers, thus farmers were monitored for a period of four years (2002 to 2005) and these data can be used to construct a before-after analysis of the training program. An additional 126 control farmers from the same four regions were selected as a control group in 2003. Control farmers were selected from areas where no intervention in aquaculture demonstration had taken place in the past and they did not receive technical support. Control farmers were monitored from 2003 to 2005 using the same approach that was followed to collect information from the project farmers. Research assistants visited each trained and control household on a bi-monthly basis to collect the information, but refrained from providing any technical information during data collection. In addition to the production monitoring, respondents kept daily records of household food consumption in a separate diary from 2003 to 2005. The survey covered information on fish consumption by species as well as the consumption of all other food items.

With funding from the Standing Panel on Impact Assessment, the same project and control farms were re-surveyed in 2012. The survey of the original project and control farmers started in March 2012 and continued to August 2012. Out of 260 original project farmers and 126 control farmers, a total of 236 project farmers and 105 control farmers were interviewed. A total of 45 farmers from the original study were not interviewed in the 2012 survey. Among the non-interviewed farmers the majority were still farming but not available for interview. Other reasons included selling of the properties and change of household organization, such as distribution of the land among the children.

In addition, in early 2013 a set of "secondary" farmers in the villages where training took place, who were not part of the original project, were also interviewed. The objective of including these other farms in the 2013 survey was to see whether the expected DSAP outcomes of higher incomes and increased fish consumption were achieved among the participants. We do not know whether the secondary farmers attended training events, but farmer-to-farmer information sharing is expected. Data were collected for 231 of these secondary farmers. An aquaculture resource census was conducted in all 42 villages before start of the 2013 survey. Based on number of project farmers in the villages an equal number of these secondary farmers were randomly selected from the list of aquaculture households. We thus have information on control farmers not in the project villages and non-participant farmers in the project villages, two groups exposed to different information dissemination pathways.

The sampled project and control farmers produced rice and various other crops, livestock (cattle, goats and poultry) and carp polyculture in ponds and rice fields. We considered only the farmers who practiced pond aquaculture with small ponds, defined as less than 0.5 hectare in area, as the target population. The Consumer Price Index (CPI) was used to inflate/deflate the cost and income figures of 2002/03 and 2012/13 to 2005/06 prices. Table 1 presents the summary statistics of the respondents by different years.

4.2 Bio-Resource Flows as an Indicator of IAA Adoption

As discussed in section 2, the target population for IAA training is small, poor farm households with pond aquaculture that are not practicing a high level of integration, and we an increase in the use bio-resource flows to represent the effects of IAA training and thus adoption of IAA practices. Table 1 shows that most farms were using some degree of integration before IAA training. Logic suggests that training would have the greatest impact on farms with low integration, and would have little or no impact on farms that have already achieved a high level of system integration. Analysis of the data confirm this hypothesis: a regression of changes in BRF on the initial level of BRF before training shows that BRF increases were highest among farms with the lowest initial level, and also shows that farms with 9 or more initial BRF did not increase BRF with training. Accordingly, we focus our analysis on the farms that have low initial levels of BRF, defined as those with initial BRF<9. The data show that farms with <9 BRF had an average BRF of 4.8 (n=188) before training, and as illustrated by the histogram in Panel (a) of Figure 4, these farms had a statistically significant average increase in BRF of 3.8 ($p<.0001$) after training. Farms with BRF ≥ 9 (n=37) had a small and statistically insignificant change in BRF from training (panel b of Figure 4).

Table 2 presents summary statistics for the sub-sample of farms with low initial integration (BRF<9). This table shows that there is a high degree of heterogeneity within the population of small pond aquaculture farms, an important factor in understanding the adoption behavior of the farms that we address belwo. The data also show that the sub-sample with low BRF produces a better match between the control and trained farms than the full sample. In the full sample, there were some farms in the control group with very high BRF, causing the mean BRF for the control group in 2005 to be higher than the trained group in 2002. After selecting out the farms with BRF greater than 8, the control group in 2005-06 had mean BRF of about 5 and the trained group had a mean of about 4.8 before training in 2002. After training, the average value was 8.6 BRF.

4.3 Heterogeneity and Adoption Behavior

The adoption model that we use in the simulation approach to *ex ante* assessment, presented in section 3, is based on the empirical observation that farms are heterogeneous, as illustrated in the data presented above. In addition, the adoption model is based on the hypothesis that farmers make economically rational decisions on average. This model implies that except under very extreme conditions, there will not be one economically dominant technology, and therefore that adoption rates are generally less than 100 percent (Antle 2011). An important implication of this model is that after the IAA training done in the DSAP program, in which farms are taught to increase the number of BRF, there are several possible outcomes:

- some farms will find IAA to be successful and maintain or increase BRF; these farms are classified as *strong adopters* of IAA;

- some farms will find a lower number of BRF than what they used in training to be economically better, but will still have a higher number of BRF than before training; these farms are also classified as adopters, and will be referred to as *weak adopters*;
- some farms will find that IAA practices are economically inferior to those associated with a lower level of integration, and thus after training will revert back to a lower number of BRF, equal to or lower than before training; these farms are classified as non-adopters of IAA.

Table 3 presents the average BRF for all farms, all adopters, strong and weak adopters, and non-adopters, for 2002, 2005 and 2012. The data confirm the patterns described above: among all trained farms, average BRF increased from 2005 to 2005, but decreased from 2005 to 2012, showing that some farms did not maintain or increase BRF. However, among adopters, BRF increased from 2005 to 2012, and among strong adopters, the increase from 2005 to 2012 was larger than the increase during the training period, whereas for weak adopters, the initial increase was very large (almost doubling their initial BRF), but then decreasing from 2005 to 2012. The net result was that strong adopters increased their BRF from 2002 to 2012 by 5.1 (121 percent), whereas weak adopters increased their BRF from 2002 to 2012 by 2.6 (47 percent). Non-adopters initially increased their BRF by 3 during training, but then decreased by 6.2, so that their BRF in 2012 was on average 45 percent lower than in 2002. Similar patterns hold for the subset of farms with initial BRF < 9.

What explains this disparate behavior? Tables 3 and 4 provide an explanation in terms of the differences in productivity and profitability among the adopter and non-adopter farms. Table 3 shows that during the training period, the productivity increases among the adopter farms were uniformly higher than among the non-adopter farms for all production activities. Table 4 shows that overall profitability of the adopter and non-adopter farms in 2002 was similar, but there were substantial differences among activities. Most notably, the non-cereal (other) crop productivity was lower for the adopter farms, and the adopter farms were much smaller than the non-adopters. Table 4 also shows that there was substantial heterogeneity among the farms in terms of initial BRF. By 2012, the non-adopter farms with high initial BRF > 9 had the highest profitability, even though their BRF declined from an average of

9.7 in 2002 to 6.3 in 2012, and their organic input use increased from 3.7 mt/ha to 5.6. In contrast, the non-adopter farms with initial low integration (BRF < 9) reduced their BRF from 5.8 in 2002 to only 2.8 in 2012, only increased organic inputs by about 20 percent, and saw a large decline in other crop profitability, possibly due to this reduced degree of integration. Nevertheless, these non-adopters achieve an overall profitability similar to the adopters. One possible explanation is that the non-adopters became more specialized and purchased more external inputs, and thus achieved a comparable profitability through a strategy that did not rely as much on integration.

In conclusion, the data show that adopters and non-adopters differed in terms of both productivity and profitability. Farms that adopted IAA achieved higher productivity, but farms that did not adopt managed to achieve equal or higher profitability through management strategies that involved less integration. These non-adopters tended to be larger farms, suggesting that the IAA technology is more suited to smaller farms where more intensive management is more effective.

4.4 Productivity Effects of Increased System Integration

The implementation of the *ex ante* analysis using the TOA-MD model requires the analyst to construct a representation of System 2 using available data for System 1 and any other relevant information. Some studies (e.g., climate impact assessments) use bio-physical simulation models to project productivity effects of exogenous changes to construct System 2. The WorldFish project provides before-after data for the project farms (comparison of the same farms before and after training) and control-treatment data (comparison of non-trained and trained). These two approaches can be implemented using statistical analysis. Table 5 presents mean relative productivities for each production activity, calculated using simple before-after and control-treatment comparisons. These comparisons were made using means for the before-after and control-treatment groups (i.e., a ratio of means), as well as using individual farm relative productivities (i.e., means of ratios). The These simple comparisons do not control for other factors that could be changing during the before-after period of 4 years, or differences between the control and treatment groups. The data in Table 5 show a wide range of productivity differences, perhaps due to the fact that there are confounding factors.

To control for confounding factors, we also estimated two econometric models to estimate productivity effects of IAA training: a fixed-effects model using the before-after data from 2002-2005; and a difference-in-difference model using the data from 2003-2005. As is well known, the fixed-effects model controls for unobserved farm-specific fixed factors, whereas the difference-in-difference model controls for such farm-specific fixed factors as well as for a common trend in productivity due to factors other than IAA training. As Table 5 shows, these two models also produced substantially different estimates of productivity effects. Looking across all of the estimates, the results confirm there are positive productivity effects of IAA but the magnitude for each type of productivity activity appears to be quite uncertain.

4.5 System Characterization and Model Parameterization for Exploratory Analysis

In estimating the TOA-MD model parameters, the farming system net returns can be constructed from data for the farm sub-systems (crop, livestock and aquaculture in this study), and a household subsystem to represent non-agricultural income and the household size. Alternatively, the data can be aggregated to the whole farm level at the outset. Depending on the way the analyst wants to use the model, each production subsystem can be further disaggregated into individual production activities (e.g., different crop, livestock or fish species). Following the data presented above, we structure the farming system as being composed of cereal crops (mainly rice), other crops, livestock and poultry, and aquaculture. The farm household is characterized by number of individuals and by off-farm income.

We use several approaches to the estimation of the parameters of the distributions of Systems 1 and 2 net returns, to explore the effects that these different approaches have on the results, and to illustrate how exploratory analyses can be implemented. The first approach is to use the observed data from farms before and after training, or for the control and trained farms, to calculate the mean net returns and the variance of returns for each activity on a per-hectare basis (for crops and aquaculture) and on a per-animal basis for livestock. The TOA-MD model is designed to then aggregate these data to the whole-farm level for the adoption and impact analyses. As shown in Table 8, these procedures were used for Models defined as M1, M1-S, and M2. These versions of the model setup used the exogenous variables as observed in each case, including prices, costs of production, farm size, household size and non-farm income. Alternatively, for the models M1-02 and M1-05 the same procedure was used except that the exogenous variables were set at values for 2002 or 2005. For the M2 model, two other variations were specified: model M2-C used mean relative productivities derived from the control-treatment comparison to specify System 2, shown in Table 4; model M2-T used mean relative productivities from the before-after groups shown in Table 4. As the table shows, these two comparisons resulted in substantially different estimates of the relative productivities. In all of these models, we used the observed correlation between returns in 2002 and 2005 to estimate the between-system correlation ρ_v. It can be shows that this method of estimating the between-system correlation is likely to be downward-biased, suggesting that testing sensitivity to this parameter would be warranted. Also, in calculating food consumption and nutritional outcomes, we used the corresponding data from each case, and used the 2002-2005 correlations between systems.

In addition to these methods, we also used the results from an econometric model similar to those presented in Table 5 to parameterize the TOA-MD model following the random coefficient setup presented in section 3.2. We implemented this procedure for whole-farm net returns rather than for the productivity of each activity. We assumed that the relative productivity β is statistically independent of System 1 production level in the population, which from equation (9) implies $\mu_2 = \mu_\beta\mu_1$, and we applied equation (10) to estimate the variance of System 2 and equation (11) to estimate the correlation between net returns of systems 1 and 2. We obtained the estimates of the mean and variance of β from the econometric model which specified net returns as a function of BRF and other covariates. Based on the parameter for BRF in the model, the average increase in net returns attributed to training was about 43 percent. We used the predicted change in net returns from this model to estimate the variance of β and the between-system correlation as in equations (10) and (11).

4.6 Model Parameterization for Out-of-Sample Extrapolation

We test the capability of the TOA-MD model to extrapolate out of sample by using the exogenous variables observed in 2012 combined with the average relative productivities observed in the before-after and control-treatment comparisons, as summarized in Table 5. In order to test the models' predictive ability, we utilize the following assumptions:

- To test the model's extrapolation capability, we assume that future prices and characteristics of the farm population are predicted accurately, and use the observed productivity effects of the training program to estimate the future productivity effects in the population. This model is defined as M1-EX- in Table 8.
- We utilize the 2002 (before training), the 2005 control (without training) and 2005 data for the trained farmers to estimate the productivity effects of IAA training, and then apply those productivity changes to estimate System 2 productivities, and standard deviations of net returns and costs, assuming these values are all proportional to the productivity effect of IAA training (see values used inTable 5).
- We utilize the farm household characteristics (farm size, non-farm income, household size, herd size, pond size, and land allocation among activities) and prices observed in 2012 for the trained farmers who were adopters, i.e, maintained increases in bio-resource flows.
- We assume that food and fish consumption for System 2 increased from 2005 to 2012 as a function of income, assuming a food income elasticity of demand of 0.5. This elasticity is in the middle of the range estimated for Bangladesh by Dey (2000).

4.7 Testing the Importance of Stratification in Predicting Distributional Impacts

The TOA-MD model is based on the assumption that when all farms in a population (or a stratified sub-population) are using the same system, outcomes in that (sub-) population are normally distributed. Many of the distributions in small farm populations are skewed, due to the influence of farm size. For example, per-farm net returns and income per capita distributions in these data are positively skewed. Potentially, this skewness could bias predictions of adoption rates and impacts using the TOA-MD model. In particular, it seems likely that predictions of threshold-based impact indicators such as poverty rates could be biased. We utilize the data in this study to investigate these questions.

One solution to the problem of skewed distributions is to recognize that skewed distributions can be represented as mixtures of symmetric distributions. In the TOA-MD model, the aggregate outcome distributions are mixtures of the systems in use, and because the distributions aggregated across strata are mixtures of the strata, the aggregate distributions in the TOA-MD model are generally non-normal. Therefore, if observed distributions of, e.g., per-capita income are non-normal, one way to improve the accuracy of the model's predictions is to stratify the population appropriately. For example, in order to achieve an accurate poverty rate when the per-capita income distribution is skewed-as it is in these data-the population could be stratified into low- and high-income groups. Related to this question, we use the case of per-capita income to test the following hypotheses:

- S1: predictions of the aggregate adoption rate are sensitive to asymmetry and stratification.
- S2: mean outcomes are robust to skewed distributions.
- S3: predictions of threshold outcomes, such as the poverty rate, are sensitive to skewed distributions.
- S4: predictions of threshold outcomes, such as the poverty rate, can be improved through stratification.

1. 5. Simulation Results and Hypothesis Tests

In this section we present the simulation results and use them to further investigate the hypotheses presented in the Introduction and outlined in Section 4. Table 8 summarizes the various models that were simulated to predict adoption rates, impacts, and test hypotheses. As discussed earlier, we utilize data for the farms with low initial integration (BRF<9), because the data show that farms with higher initial integration were already effectively adopters, and also were larger farms with higher incomes, and thus not the target population for the training program. To investigate robustness to assumptions, models using both before/after and control/trained data were simulated, as well as models extrapolating from 2005 to 2012. Models with data stratified by low- and high-incomes (which also correspond to small and large farms) were also simulated. Table 9 summarizes the simulation results for the full population (aggregated across non-adopters and adopters) to illustrate differences in the various model setups. Disaggregated results are presented in Table 10 for impact indicator values and treatment effects for small and large farms (differences between values for non-adopters and adopters and their counterfactuals). Figures 6-11 illustrate some of the results. Figure 6 shows the plot of the "adoption curves" for model M1-EX that show the predicted adoption rate under the assumption that farmers choose the system with the highest economic value (i.e., for adoption threshold parameter *a* = 0), or where the opportunity cost is equal to zero and the curve crosses the horizontal axis The other figures plot impact indicators against adoption rates ranging from zero to 100 percent that are constructed by varying the adoption threshold over its range from minus to plus infinity.

5.1 Tests of Hypotheses

In this section, drawing on the hypotheses detailed in the study proposal, we summarize the results of hypotheses tested.

H1*: DSAP recommended practices for IAA technologies are economically feasible for more than 50 percent of the target population of small farms for which pond aquaculture is technically feasible.*

Confirmed. Table 9 shows that the predicted adoption rates are in the 60-72 percent range for this sample of small farms that had low initial integration. Further stratification of this sample into low-and high-income groups (which further subdivides the sample into very small and somewhat larger farms) shows that similar adoption rates are predicted for these groups.

H2: *Incomplete adoption of IAA technologies is explained by: (a) average productivity and/or cost of production; (b) high variability in productivity and/or cost of production.*

Confirmed. Sensitivity analysis was carried out to investigate effects of average productivity and cost of production on adoption rates. Figure 6 shows the effects of alternative assumptions on the "adoption curve" constructed by simulating the difference in expected returns between Systems 1 and 2 for model M1-EX. Note that the reduction in heterogeneity makes the curve "flatter" and thus increases the adoption rate for given mean returns, whereas the increase in mean returns to System 2 due to higher productivity shifts the curve downwards and thus increases the adoption rate. This analysis shows, using model M1-EX, that an increase in productivity of all activities (crop, livestock, fish) of 50 percent would increase adoption rates above 80 percent. Reducing the spatial heterogeneity of returns by 50 percent, and increasing the consistency of training (in the model, increasing the correlation between system returns from 0.75 to 0.9), increases the adoption rate to 76 percent. The combination of these two changes would raise the adoption rate to about 91 percent.

H3: *Adopters of IAA technologies have lower poverty and better nutrition than non-adopters.*

Confirmed. See Tables 9 and 10.

H4: *(a) Adoption and (b) impacts of IAA technologies are the same for small and large farms.*

(a) confirmed; (b) rejected. Adoption rates were similar for small and large farms, stratified by income; however, impacts differ by income and farm size groups (Table 10). Poverty rate reductions and increases in fish consumption are much higher for smaller, poorer farms (Figures 10-11).

H5: *The TOA-MD model predicts adoption rates sufficiently well for use in ex ante and ex post impact assessment.*

Confirmed. First, we note that a key implication of the heterogeneous population model is that the predicted adoption rate for a technology with higher expected mean net returns will be between 50 percent and 100 percent. The 2012 data show 68.8 percent of trained farms had an increase in bio-resource flows compared to 2002 (Table 2). Table 9 shows that the TOA-MD model predicts an adoption rate of 69.8 percent, based on the before-after data from 2002 and 2005 for the trained group, or an adoption rate of 70.7 percent based on the without/with comparison of the 2005 control group versus the 2005 trained group. The various other models presented in table 9 predict somewhat lower adoption rates. The extrapolation model predicts an adoption rate of about 63 percent.

H6: *The TOA-MD model predicts aggregate impacts accurately without knowing adoption-outcome correlations.*

Confirmed for non-income outcomes; rejected for income-related outcomes. As Figure 2 shows, prediction of indicators for adopters, non-adopters, and the entire population depends in part on the correlations between ω (the opportunity cost of changing systems) and the outcome *k*. Depending on the configuration of these parameters, the aggregate outcome indicator may have a linear relationship with the adoption rate, such that the aggregate indictor can be expressed as a linear combination of the mean for System 1 and the mean for System 2, the weights equal to the adoption rate and one minus the adoption rate. As illustrated by Figure 9 for aggregate food consumption and Figure 10 for fish consumption, some outcome variables exhibit this linearity property. However, other outcomes were more sensitive to correlations with system returns and thus exhibit non-linear relationships with the adoption rate (see Figures 7, 8 and 11).

H7: *Impacts within adopter and non-adopter sub-populations can be predicted accurately without knowing adoption-outcome correlations.*

Rejected. The results show that for some outcomes, such as food consumption, correlations were very low and therefore outcomes for non-adopter and adopter sub-populations could be predicted accurately by the means of the control and treated groups, respectively. However, for all other outcomes, including fish consumption and all income-related outcomes such as poverty rates and per-capita income, this hypothesis is strongly rejected. Note that zero correlations would imply that the curves for the adopters and non-adopters in Figures 7-11 would be horizontal; visual inspection shows this is clearly not the case for all of the outcomes variables except food consumption where indeed the correlations are low.

S1: *predictions of the aggregate adoption rate are sensitive to asymmetry and stratification.*

Rejected. The predicted adoption rates were similar for models estimated with the entire population and the population stratified by farm income and size groups (Table 9).

S2*: predictions of mean outcomes are robust to skewed distributions.*

Confirmed. Table 9 shows that mean outcomes are reasonably similar for models not stratified and stratified.

S3: *predictions of threshold outcomes, such as the poverty rate, are sensitive to skewed distributions.*

Confirmed. See Tables 2 and 9, which show that poverty rates are under-estimated for the models that are not stratified, but are estimated accurately in the aggregate when the population is stratified by income groups.

***S4:** predictions of threshold outcomes, such as the poverty rate, can be improved through stratification.*

Confirmed. See Tables 2 and 9 and comment on S3.

6. Conclusions

As summarized in the introduction, this study demonstrated and evaluated the simulation-based approach to technology impact assessment, using previously collected data and a new follow-up survey for farms trained in the use of IAA. While the study did not aim to evaluate the implications of IAA beyond the study areas represented in these data, the findings also have implications for WorldFish's IAA training program and the usefulness of IAA in the ongoing economic development of agriculture in Bangladesh. This assessment finds compelling evidence that the IAA methods have been adopted in the villages where training took place and have had large positive impacts on small-holder farm households in terms of their incomes and their nutrition, subject to the caveats we have discussed regarding the limitations of the available nutritional data. Based on the concept of bio-resource flows (BRF) used by WorldFish in its training programs, the adoption rate of IAA (meaning that farms increased the degree of integration on their farms) was found to be near 70 percent in 2012, six years after the training program, and there appears to have been similar adoption by non-participant farms in the villages where training took place. Another finding is that adopters and non-adopters differed in terms of both productivity and profitability. Farms that adopted IAA achieved higher productivity, but farms that did not adopt managed to achieve equal or higher profitability through management strategies that involved less integration. These non-adopters tended to be larger farms, suggesting that the IAA technology is more suited to smaller farms where more intensive management is more effective. The control farms also substantially increased the number of bio-resource flows, but did not increase their use of organic inputs much, and did not achieve the same economic improvements as the farms in the villages where IAA training took place. This raises some important questions about the dissemination of IAA beyond the areas where training took place, but due to the small number of farms in the control group, it is difficult to know if these findings regarding the control group are valid or can be generalized.

The main goal of this study was to use the original assessment data and the follow-up data to test the validity and usefulness of the simulation-based approach to impact assessment. In this study we defined adoption of IAA as an increase in bio-resource flows on farms with low levels of integration before they were trained in the use of IAA practices. The simulation analysis predicts an adoption rate in the neighborhood of 70 percent, close to the observed adoption rate. We also found that predicted impacts of IAA adoption are similar to those observed in the villages where IAA training took place in the follow-up survey carried out in 2012, six years after the training. Based on the results reported here and summarized in section 5 and the introduction, we conclude that the model's usefulness has been substantiated. While this test of the simulation-based approach to *ex ante* assessment is encouraging, testing in other settings is needed to further validate the approach and also to further explore the many methodological issues that have been raised in the present study. Finally, we note that this modeling approach can also be used to project impacts of climate change on agricultural systems and households. A major new study demonstrates this use of the TOA-MD model to assess climate vulnerability of agricultural systems in Sub-Saharan Africa and South Asia (Rosenzweig and Hillel 2015).

Table 1: Summary Statistics from the Sample Data for the DSAP Training Program Study and the SPIA follow-Up Study(means with standard deviations in parentheses) (BDT is Bangladesh Taka)

Year	2002/03	2005/06		2012/13		
Farmer	Project farmers	Project farmers	Control farmers	Project farmers (follow-up)	Control farmers (follow-up)	2013 survey farmers
Crop area (ha)	.82 (.79)	.82 (.76)	.69 (.51)	.63 (.61)	.64 (.62)	.58 (.40)
Pond area (ha)	.12 (.18)	.13 (.19)	.16 (.27)	.16 (.24)	.11 (.15)	.12 (.13)
Herd Size (animal no.)	28 (71)	25 (38)	22 (24)	23 (58)	21 (36)	22 (25)
Crop income (BDT/ha/yr)	33,825 (26,909)	62,506 (35,276)	45,431 (38,438)	58,463 (58,083)	38,188 (33,106)	63,570 (1,51,391)
Fish income (BDT/ha/yr)	34,166 (32,515)	77,548 (41,693)	34,404 (34,667)	107,718 (68,938)	81,554 (74,859)	100,799 (66,149)
Animal income (BDT/animal/yr)	67 (406)	212 (537)	120 (200)	403 (2,088)	86 (1,998)	-13 (1,540)
Non-farm income (BDT/yr)	47,119 (43,350)	53,706 (54,950)	43,050 (44,149)	59,280 (68,275)	49,677 (75,786)	57,718 (77,563)
Poverty rate[1] (percent)	50.7	35.1	58.5	32.7	51.5	40.0

[1] Poverty rate is calculated considering the 2005 conversion value of $1.25/day PPP equivalent to BDT 31.86 (Bangladesh Taka) and 2005 exchange rate to BDT 62 per US dollar, the poverty line was set as BDT11,629 ($187) per year. An estimated 45-50 percent of Bangladesh's 150 million people reportedly live below the international poverty line of 1.25 U.S. dollars a day (Index Mundi, 2012).

Household members	6.07 (2.38)	6.14 (2.37)	6.35 (2.54)	5.95 (2.47)	5.71 (2.23)	5.65 (2.60)
Bio-Resource flows (BRF) (no.)	5.62 (2.62)	8.94 (1.11)	7.78 (3.55)	7.49 (3.96)	8.01 (3.56)	7.31 (4.01)
Food consumption (gm/person/day)	n.a.	848 (226)	773 (216)	997 (291)	995 (275)	973 (361)
Fish consumption (gm/person/day)	n.a.	57 (28)	44 (22)	68 (36)	66 (42)	65 (33)
Organic fertilizer use (Kg/ha/year)	2,496 (2,168)	3,063 (2,389)	2,895 (2,079)	4,074 (5,372)	2,991 (2,478)	4,138 (4,707)
Number of households	225	225	123	220	103	217

Source: Authors' calculations from DSAP and SPIA survey data. Poverty rate is the headcount poverty rate based on per-capital income using a poverty line of 11,629 BDT.

Table 2. Data for Sample of Farms with Low Initial Integration Used to Parameterize the TOA-MD Simulation Model (BRF<9)

	T2002 (before training)	C2005 (control)	T2005 (trained)	T2012	C2012	S2012
Bio-resource flows (number)	4.84	5.02	8.58	7.41	8.67	7.21
Farms with BRF increase > 0 (%)	n.a.	n.a.	92.8	68.8	81.4	n.a.
Farms with BRF increase > 1 (%)	n.a.	n.a.	82.9	61.1	69.8	n.a.
Farm size (ha)	0.83	0.59	0.84	0.68	0.64	0.7
Net returns (BDT/ha)	34885	46526	71938	72103	42226	67806
Income (BDT/person)	13066	12258	17977	20576	13861	20418
Poverty rate (%)	55.5	62.1	39.2	34.4	53.3	40.7
Food consumption (gm/person/day)	n.a.	730	834	996	952	981
Fish consumption (gm/person/day)	n.a.	36	53.3	69.3	73	64.6
Organic fertilizer (kg/ha)	2273	2472	2934	3766	2536	4168
Number of observations	181	58	181	157	43	204

Note: T = group of farms that were trained to use IAA; C = control farms; S = secondary (non-trained) farms in villages where training was done.

Table 3. Average Relative Productivities and BRF Changes for IAA Trained and Control Farms

	Trained Farms					Control Farms	
	All	Adopters	Strong Adopters	Weak Adopters	Non-Adopters	2003	2005
Cereal Crops	1.41	1.49	1.51	1.46	1.31	1.47	1.07
Other Crops	1.08	1.33	1.44	1.16	0.88	1.06	1.86
Fish	1.98	2.03	2.02	2.04	1.92	1.64	1.55
Livestock	1.16	1.29	1.17	1.43	1.07	1.59	2.06
Poultry	1.14	1.35	1.28	1.48	0.88	0.84	1.68
∆BRF 2002-2005	3.27	3.43	2.59	4.92	3.03	0.61	0.61
∆BRF 2002-2012	1.82	5.07	6.49	2.56	-3.14	3.44	3.44
Number of observations	179	108	69	39	71	51	51

Note: Relative productivity for trained farms defined as average production per ha in 2005 relative to 2002, for control farms defined as average production per ha in 2003 or 2005 relative to average trained farm production in 2002.

Table 4. Economic Characteristics of IAA Adopters and Non-Adopters, 2002, 2005 and 2012

			Non-adopters	
		Adopters	Low BRF	High BRF
2002	Area (ha)	0.76	0.86	1.4
	BRF	4.7	5.8	9.7
	Org input (t/ha)	2.3	2.5	3.7
	NR/ha (1000 BTK)	34.3	35.5	34.1
	Crop NR/ha	23.4	31.8	25.1
	Other crop NR/ha	65.3	105.6	73.7
	Fish NR/ha	32	32.8	37.3
2005	Area	0.78	0.89	1.4
	BRF	8.1	9.8	10.9
	Org input	2.9	3.1	4
	NR/ha	70.8	71.2	62.6
	Crop NR/ha	48.8	52.8	46.5
	Other crop NR/ha	120.6	148.8	127.6
	Fish NR/ha	73.7	76.3	82.4
2012	Area	0.66	0.76	0.96
	BRF	9.7	2.79	6.3
	Org input	3.9	3.1	5.6
	NR/ha	66.6	68.1	96
	Crop NR/ha	27.9	30.4	46.8
	Other crop NR/ha	118	81.5	185
	Fish NR/ha	102.3	95.8	210.4
	Number of Obs	108	48	23

Table 5: Percent change in average productivity of trained farmers using alternative methods, and values assumed for extrapolation

	Cereals	Other crops	Ponds	Livestock	Poultry
After/before relative productivity (ratio of means) 2002-2005	41	15	102	28	17
After/before relative productivity (mean of ratios) 2002-2005	44**	31**	97**	-3	-3
Fixed effect model for productivity differences 2002-2005	36*	29	188**	-5	225
Treatment/control relative productivity (ratio of means) 2005	-2	34	40	53	104
Diff-in-Diff model for treatment/control productivity differences 2003-2005	28*	25	30	49*	87
Assumed relative productivity for extrapolation	30	30	70	60	60

Table 6. Simulation Model Definitions

	System 1	System 2
M1	Project farms in 2002 before training	Project farms in 2005 after training
M1-02	Project farms in 2002 before training	Project farms in 2005 after training, exogenous variables set at 2002 values
M1-05	Project farms in 2002 before training, exogenous variables set at 2005 values	Project farms in 2005 after training
M1-S	Same as M1 stratified by income	Same as M1 stratified by income
M1-AD	Project farms in 2002 before training	Project farms in 2002, productivity effects estimated using random coefficient model based on econometric results in Table 6
M2	Control farms in 2005	Project farms in 2005 after training
M2-C	Control farms in 2005	Control farms in 2005, effect of training estimatted with control-trained productivity differences by activity (Table 4)
M2-T	No-training counterfactual estimated with before-after productivity differences by activity (Table 4)	Project farms in 2005 after training
M1-EX	Trained group extrapolated to 2012 using exogenous variables observed in 2012	Trained group extrapolated to 2012 using productivity differences by activity in Table 4

.

Table 7. Simulation Model Results for All Farms with Low Initial Integration

	M1	M1-02	M1-05	M1-S	M1-AD	M2	M2-C	M2-T	M1-EX
Adoption rate (%)	69.8	61.7	62	71.6	60	70.7	59.8	60.4	63.2
Net returns (BDT/ha)	67367	59779	69546	67537	55335	67994	58737	70023	95235
Income (BDT/person)	17402	15621	18125	18770	17187	17277	14766	18292	19334
Poverty rate (%)	34.7	37.5	32.5	37.1	35.5	35.1	39.8	32	31.3
Food consumption (gm/person/mo)	811	805	805	827	896	804	793	793	1029
Fish consumption (gm/person/mo)	49.4	48.4	48.4	51	58.5	48.4	46.5	46.6	67.7
Organic inputs (kg/ha)	2622	2554	2554	2982	2845	2760	2705	2708	3591
Bio-resource flows	7.97	7.71	7.72	7.6	7.37	7.89	7.53	7.55	7.42

Note: see Table 6 for Model definitions. Bio-resource flows are number of flows between system components.

Table 8. Base values of Indicators, Values of Indicators for Small and Large Farm Adopters and Non-adopters for Scenario M1-S

			Adopters			Non-adopters		
Small Farms	Base	ATE	Value	CF	TT	Value	CF	TU
Net returns (BDT/ha)	21687	23744	66906	19192	47714	22128	-6891	-29019
Per-capita income (BDT/person/yr)	7600	1091	16699	6590	10109	7946	3602	-4344
Poverty (%)	78.1	-33.7	36.5	84.4	-47.9	76.7	84.8	8.1
Food consumption (gm/person/day)	673	98	753	665	88	691	814	123
Large Farms								
Net returns (BDT/ha)	37862	19055	78726	44621	34105	20320	310	-20010
Per-capita income (BDT/person/yr)	23543	4614	32873	21406	11467	23543	13621	-9922
Poverty (%)	21.4	-1.6	13.8	25.9	-12.1	28.3	45.2	16.9
Food consumption (gm/person/day)	841	71	937	865	72	781	848	67

Note: ATE = average treatment effect; CF = counterfactual value; TT = treatment effect on the treated (adopters); TU = treatment effect on the untreated (non-adopters)

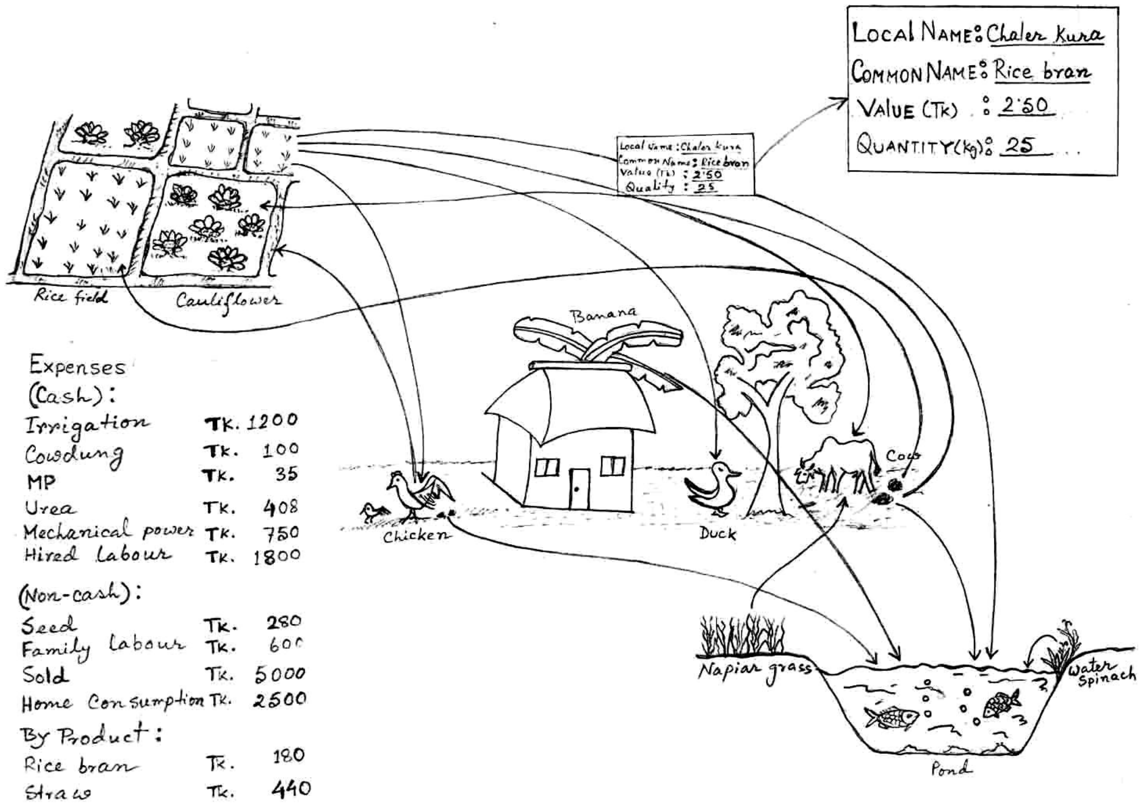


Figure 1: Farmer-prepared bio-resource flow diagram. The general profile of the enterprises, species list and input and output data are recorded. The arrows represent the direction of the material flows between enterprises and natural resource types within a farming system.

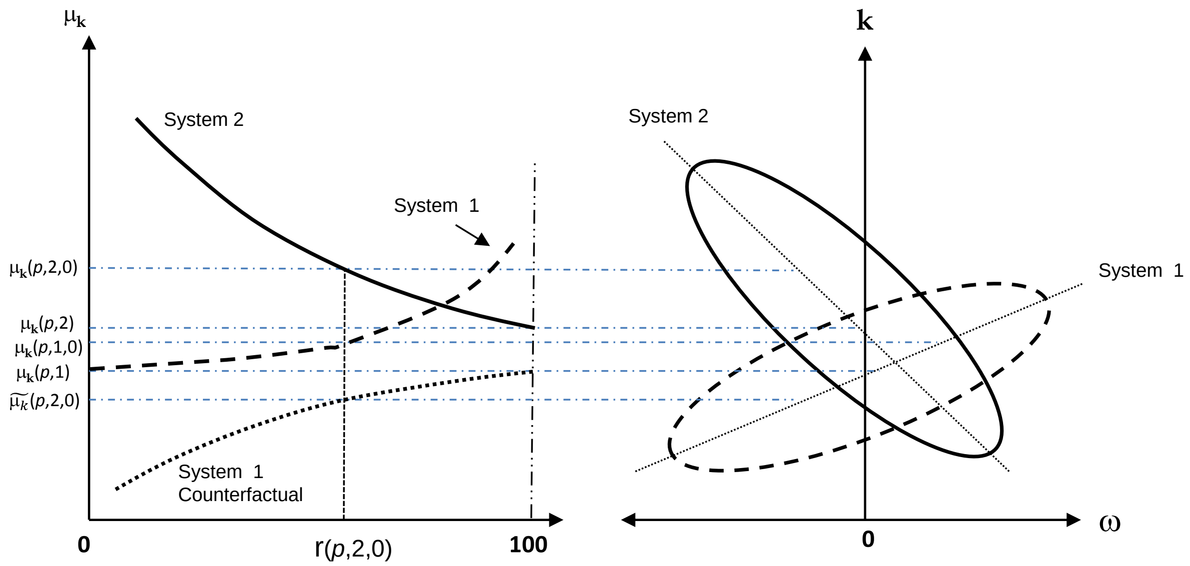


Figure 2. Derivation of Mean Impact Indicators and Treatment Effects from the Joint Distribution of opportunity cost ω and and outcome k. See Section 3.2 for definitions.

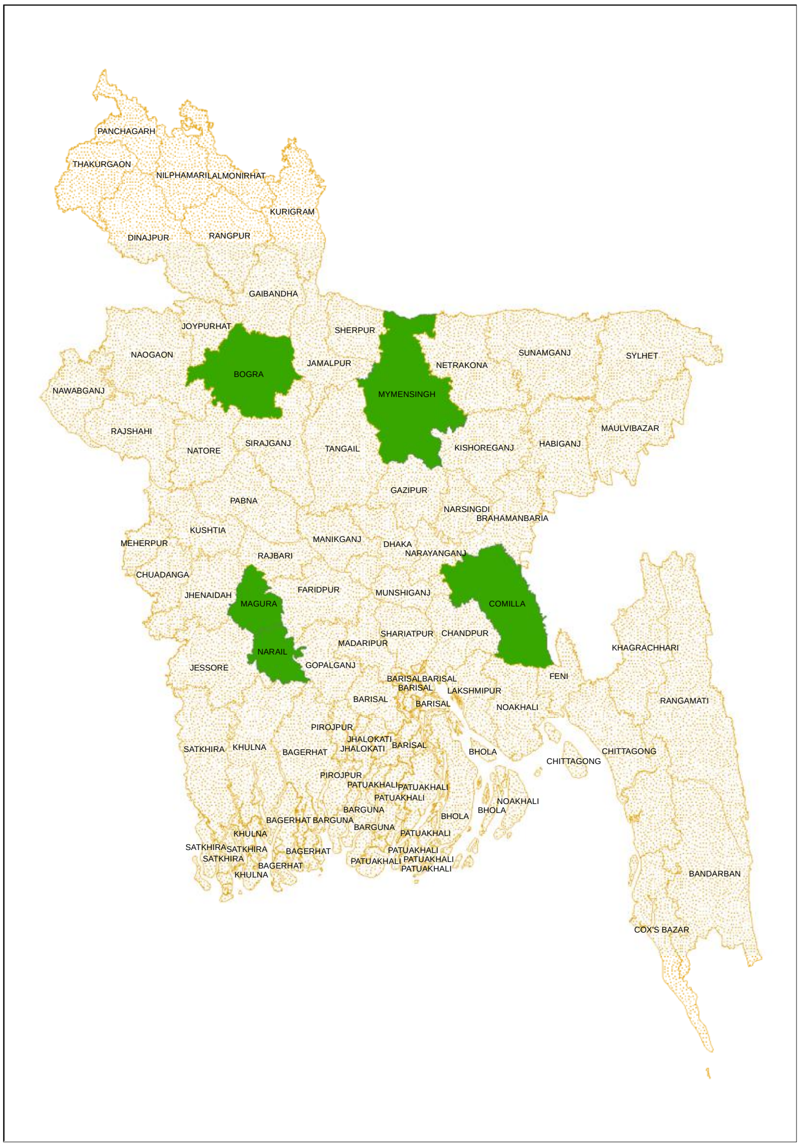
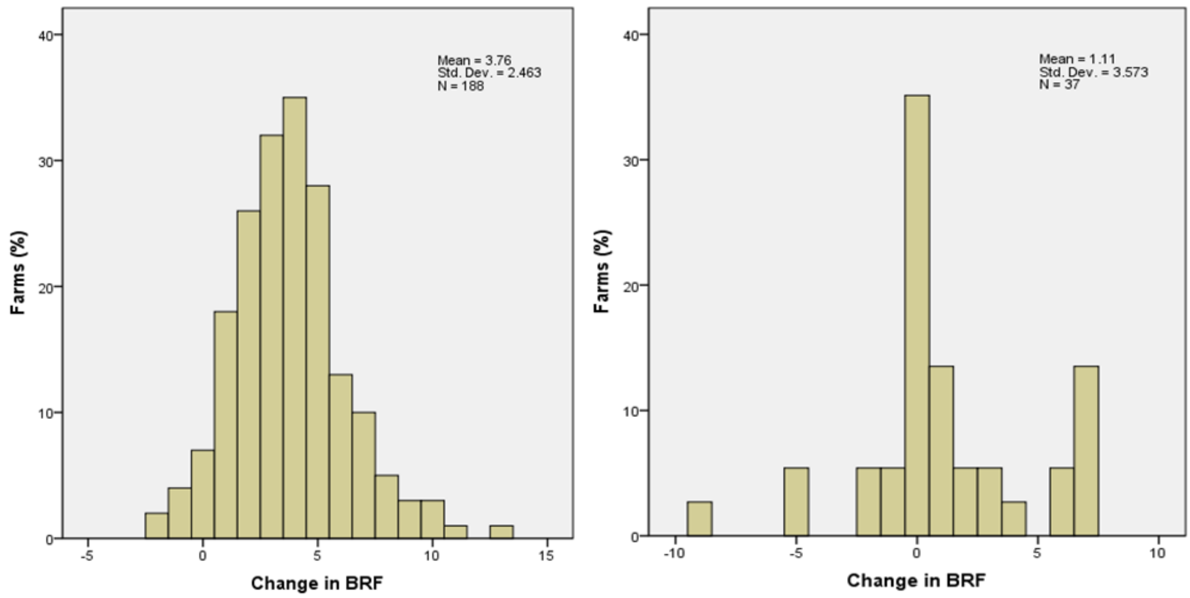
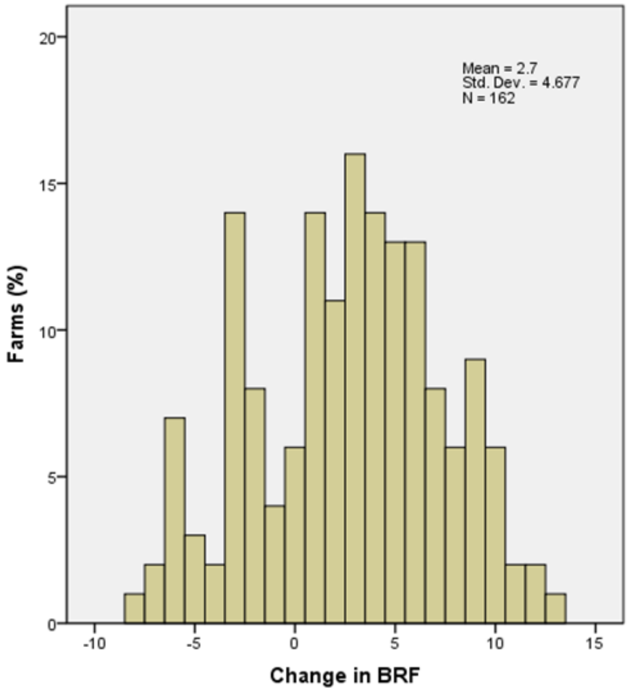


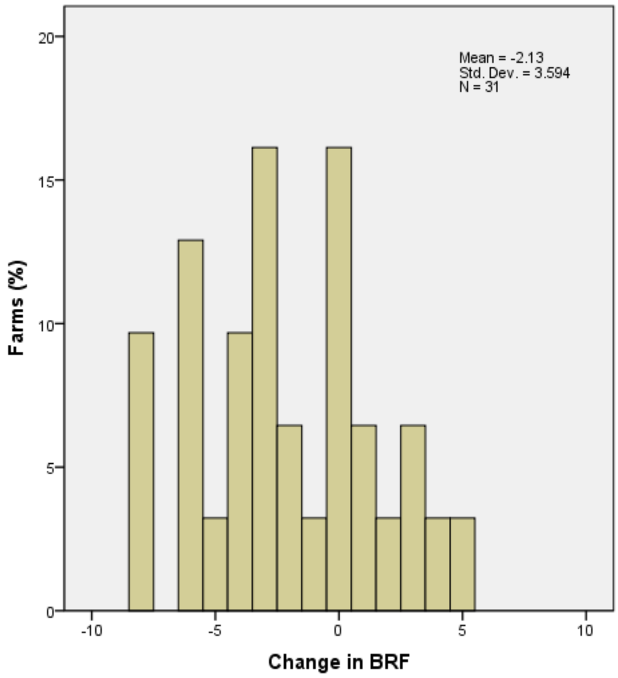
Figure 3: Map of Bangladesh and the DSAP survey study areas: Mymensingh,
Comilla,
Magura and Bogra



(a) (b)

Figure 4: Change of Bio-Resource Flows (a) among Low Bio-Resource Flow farms and (b) among High Bio Resource Flow farms, from 2002 to 2005.





(a) (b)

Figure 5: Change of Bio-Resource Flows (a) among Low Bio-Resource Flow (LBRF) farms and (b) High Bio Resource Flow farms, from 2002 to 2012.

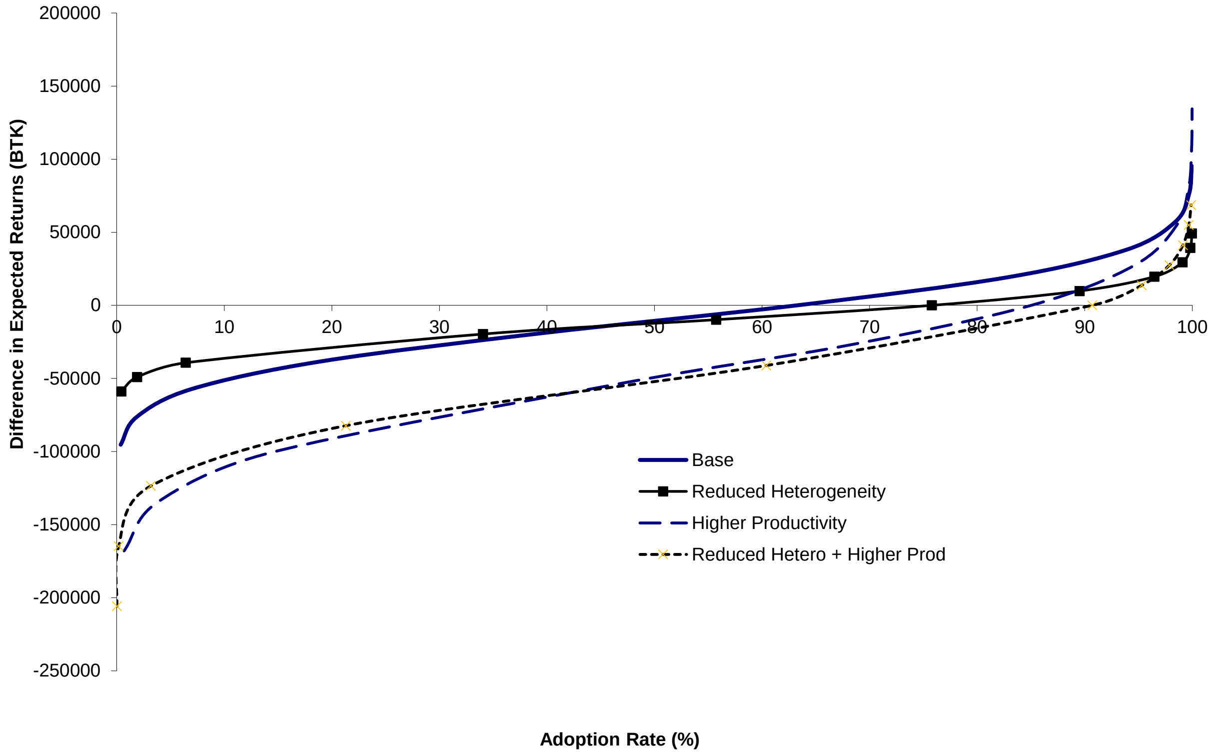


Figure 6. Effects of Reduced Heterogeneity and Higher Productivity on Adoption of IAA, using Model M1-EX. Predicted adoption rate is where difference in expected returns between the two systems is zero (where the curve crosses the horizontal axis).

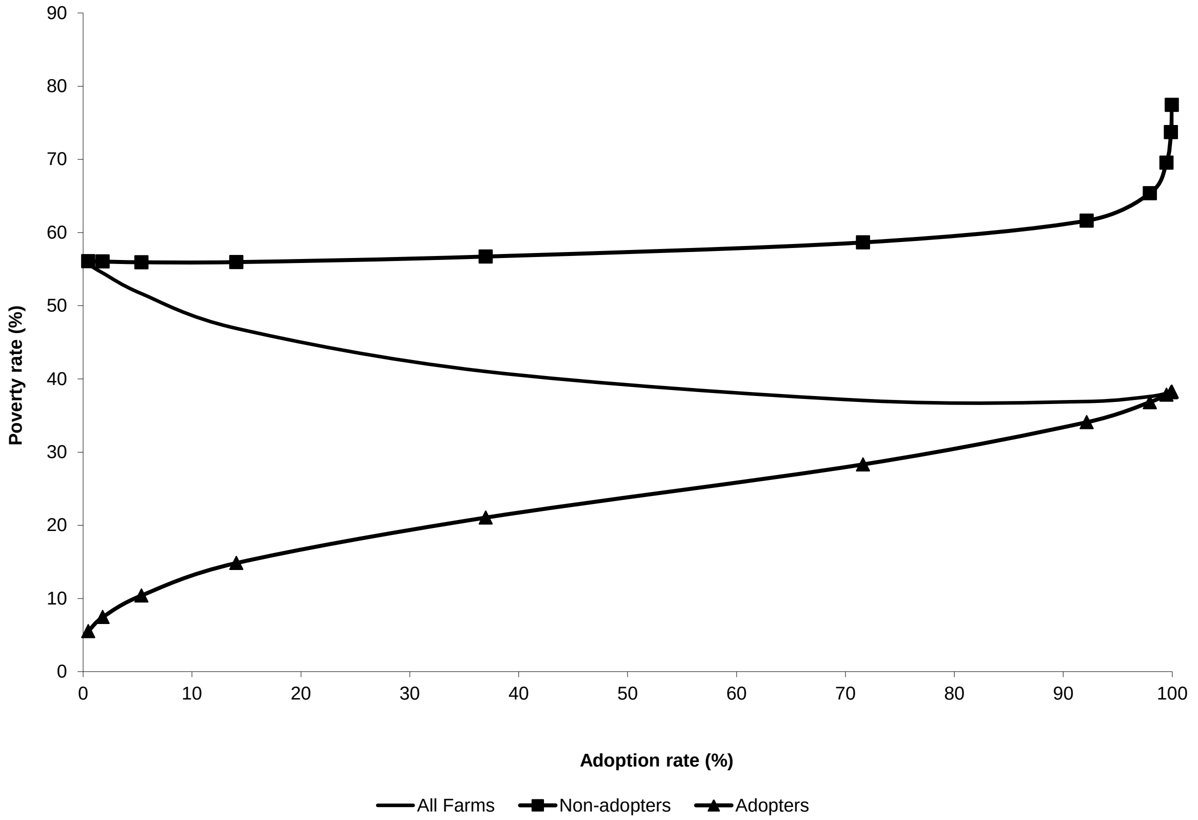


Figure 7. Simulated poverty rates based on Model M-1 and the population stratified by low (<12,000 Tk) and high income per capita.
Observed poverty rate was 55.5 percent before training, simulated poverty rate before training is 56 percent. Observed poverty rate among the trained farmers after training was 39 percent, predicted rate is 38.3 percent. Predicted adoption rate is 71.6 percent, predicted poverty rate among adopters is 28 percent, predicted poverty rate among non-adopters is 58.7 percent. A linear interpolation (assuming zero correlations between adoption and income) would imply a predicted poverty rate in the overall population of about 44 percent, whereas the model with non-zero correlations implies an overall poverty rate of 37 percent.

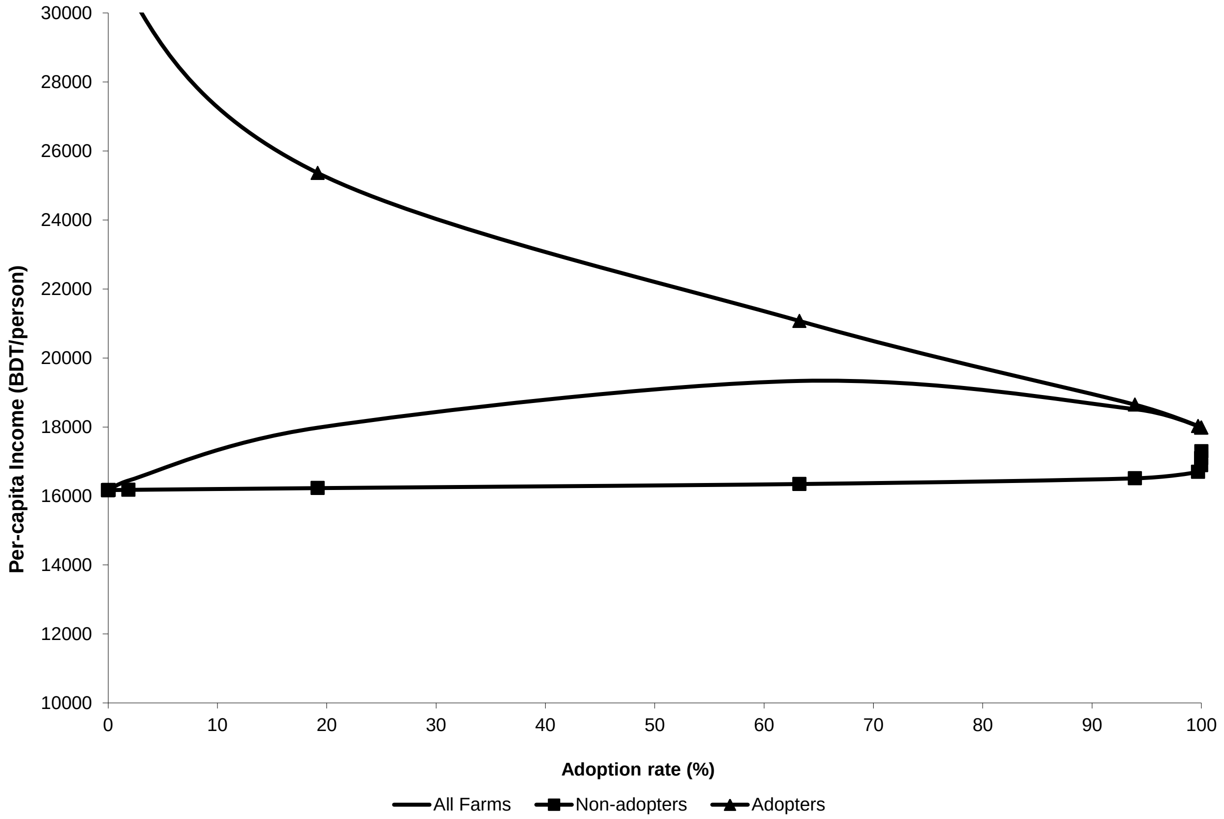


Figure 8. Simulated Per-capita income for model M1-EX, extrapolating the simulation analysis from 2005 to 2012 for the trained farms.
Note that the observed mean income in 2012 for the trained farms was observed to be 20576, the value predicted by the model extrapolation is 19334. The predicted adoption rate is 63.2 percent for this group; the percentage of farms with an increase in bio-resource flows compared to per-training is 68.8, the percentage with an increase of more than 1 bio-resource flow is 61.1. Also note that the negative correlation between opportunity cost of System 2 and adopter income results in the negatively sloped relationship for the adopters shown here, and also causes the curve for all farms to be maximized at the predicted adoption rate of 63.2 percent.

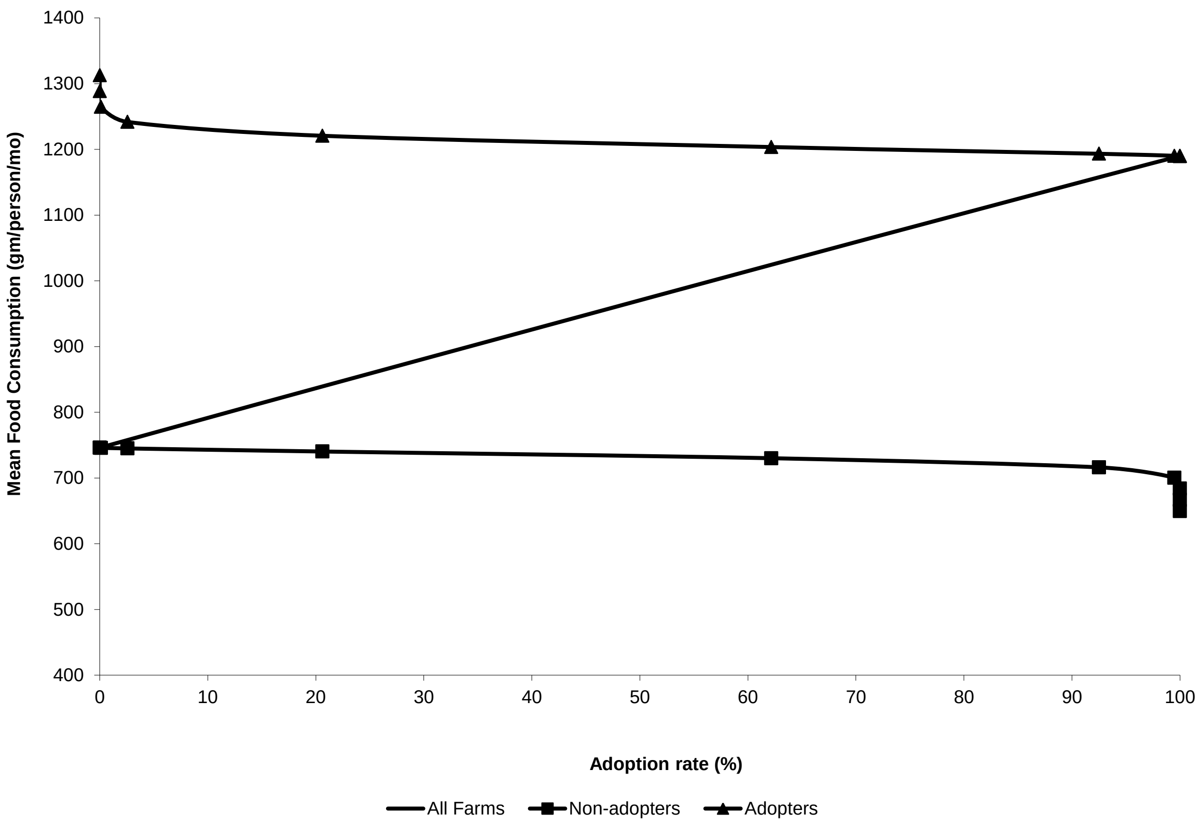


Figure 9. Mean food consumption using Model M1-EX
This figure shows the effects of the low correlation between food consumption and system returns (the horizontal curves for non-adopters and adopters, and the nearly linear curve for all farms).

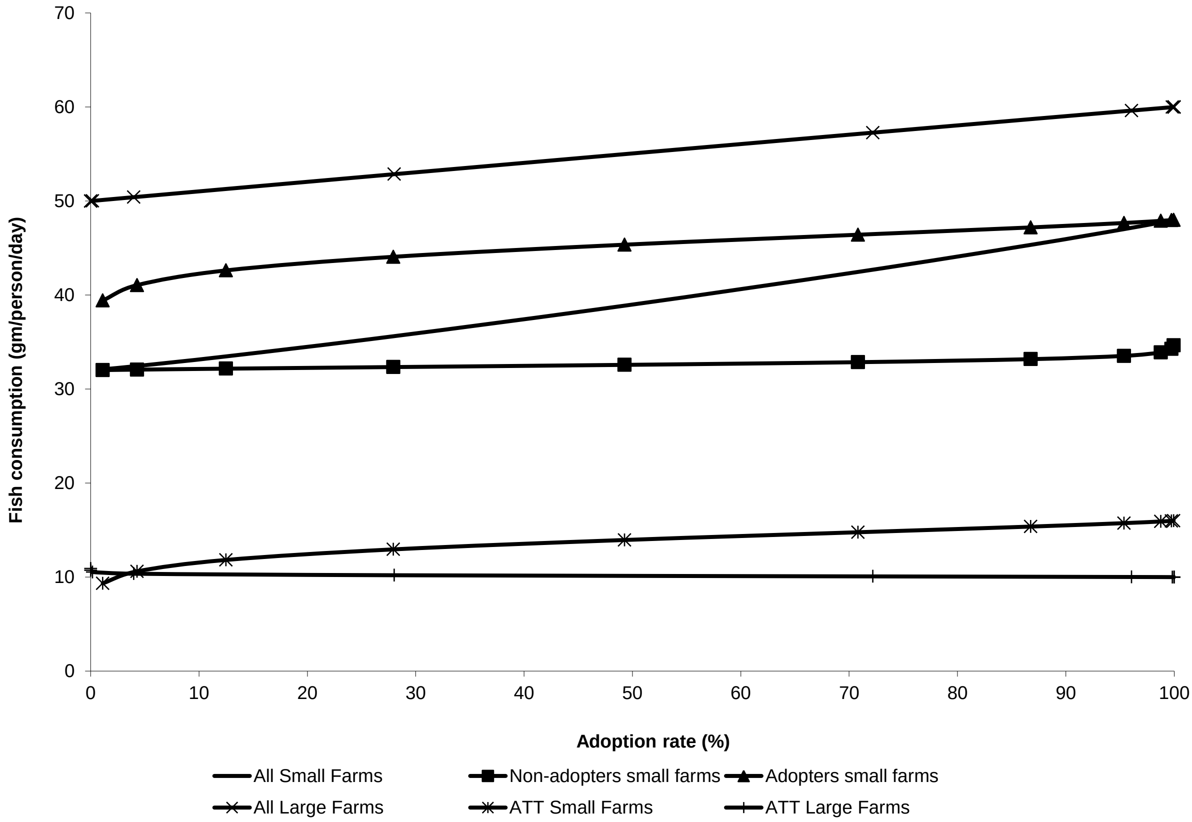


Figure 10. Predicted Fish Consumption for Small and Large Farms, Non-adopters and Adopters (note: ATT = average treatment effect on the treated = increase in consumption for adopters)

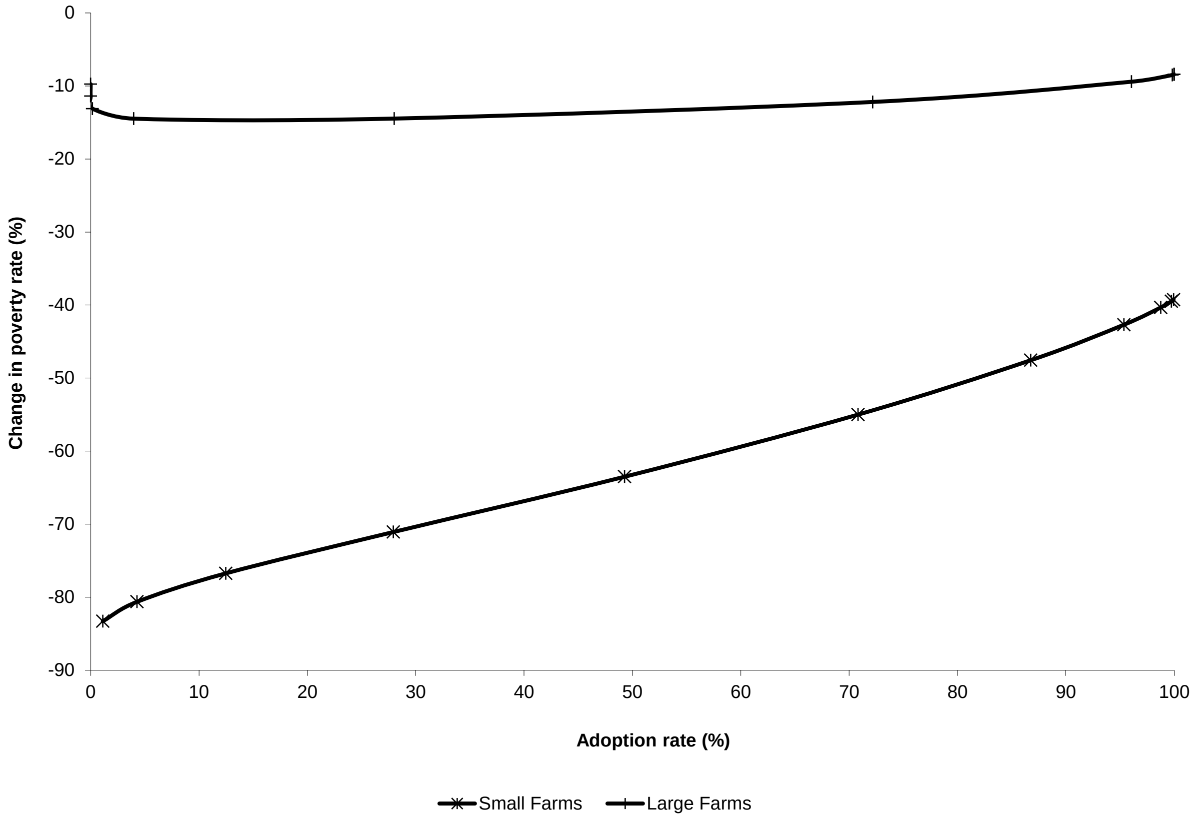


Figure 11. Poverty reduction effects of IAA for small and large farm adopters

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