Received: 27 June 2021 | Accepted: 14 September 2023

DOI: 10.1111/1467-8489.12537

The Australian Journal of Agricultural and Resource Economics | AARES Australasian Agricultural & Resource Economics Society

ORIGINAL ARTICLE

Conservation agriculture-based sustainable intensification improves technical efficiency in Northern Bangladesh: The case of Rangpur

Bruno Paz[1] | **Atakelty Hailu**[2] | **Maria Fay Rola-Rubzen**[2] | **Md Mamunur Rashid**[3]

[1]University of Göttingen, Göttingen, Germany

[2]UWA School of Agriculture and Environment, The University of Western Australia, Crawley, Western Australia, Australia

[3]RDRS Bangladesh, Dhaka, Bangladesh

Correspondence
Bruno Paz, University of Göttingen, Heinrich-Düker-Weg 12, Göttingen 37073, Germany.
Email: brunopazg@gmail.com

Funding information
Australian Centre for International Agricultural Research, Grant/Award Number: CSE/2011/077

Abstract

The dissemination of conservation agriculture (CA) technologies has become the objective of a growing number of projects aimed at reducing food insecurity in vulnerable areas of the world. While many studies have found that CA increases farm productivity, little is known about the components of the productivity gains related to CA adoption. CA is a knowledge-intensive technology, and it is expected to affect both technical efficiency (TE) and input productivity positively. Using cross-sectional farm-level data of 220 maize farmers in Bangladesh, we measure the impact of CA on farmers' TE. We first apply propensity score matching (PSM) to create comparable counterfactual groups of CA and non-CA farmers. Then, we use a stochastic frontier with correction for self-selection bias to analyse TE. Finally, we fit a stochastic meta-frontier (SMF) model to the data and use it to compare TE across the two farmer groups. The analysis showed that CA farmers exhibit greater TE levels than non-CA farmers. This can be attributed to enhancements in farm management, leading to 8% and 9% increases in their productivity and TE, respectively. Thus, there is a case for policymakers to strengthen programs delivering CA technologies that improve food security in Bangladesh.

KEYWORDS

conservation agriculture, meta-frontier analysis, self-selection bias, South Asia, technical efficiency

JEL CLASSIFICATION
Q160, D240

1 | INTRODUCTION

A growing number of international organisations have development programs and projects centred around promoting and disseminating conservation agriculture (CA). CA is composed of three agricultural practices: (i) zero tillage, (ii) crop rotation and (iii) permanent soil cover (Hobbs, 2007). Several studies have found that CA increases agricultural productivity (Chan et al., 2017; Dixon et al., 2020; Hassane et al., 2000; Huang et al., 2008; Kassam et al., 2009; Ndlovu et al., 2014; Tessema et al., 2018; Tsegaye et al., 2008).

Agricultural productivity growth is primarily the result of technological change and efficiency improvement (Bravo-Ureta et al., 2007). Technical change is defined as a source of productivity growth when a technological improvement shifts the production frontier upward (Coelli et al., 2005). Likewise, a farm becomes more technically efficient when it can get more output for its inputs due to improvements in farm management or the reallocation of resources within the farming system (Bravo-Ureta et al., 2007). Therefore, farming knowledge and education are expected to increase technical efficiency (TE) (Asadullah & Rahman, 2009; Haider et al., 2011).

CA is considered a farming knowledge-intensive technology (Kassam et al., 2009; Wall, 2007), and its success mainly depends on farmers' management rather than on the quantity of inputs applied (Ekboir et al., 2002). Thus, we can expect that adopting CA positively affects farmers' managerial ability (TE). Still, the impact of CA on farmers' TE is contentious. Solís et al. (2007) and Krishna and Veettil (2014) concluded that CA had a positive impact. Oduol et al. (2011) and Ndlovu et al. (2014) did not support these findings and concluded that CA negatively impacts farmers' TE and is not significant, respectively. However, most of these studies failed to correct for selection bias from observed and unobserved variables and to consider the technology differences across groups. For example, Chan et al. (2017) selected participants for their study based on their poor socio-economic situation, the potential for improvements to their agricultural production systems and existing nongovernmental organisation. Thus, the data were subject to sample selection biases. Solís et al. (2007) addressed self-selection biases using the inverse Mills ratio (IMR), an approach derived from Heckman (1979), which is not suitable for nonlinear models such as stochastic production frontiers (SPFs; Greene, 2010).

This study examines the impact of CA on the TE and productivity of Northern Bangladeshi farmers allowing for self-selection bias and technology differences. It makes three main contributions. The first is to help expand the limited empirical research examining how CA affects farmers' TE in Northern Bangladesh. The second is a better understanding of productivity effects when CA is adopted only partially. The third is to improve our knowledge of the determinants of CA technology adoption and help inform strategies for scaling up CA technology.

The paper is organised as follows. The next section reviews the literature on CA. The analytical framework is presented in Section 3. The description of the data sources and the empirical model follow in Section 4. In Section 5, we present and discuss our results. Section 6 concludes the paper.

2 | BACKGROUND

2.1 | Conservation agriculture

Interest in CA grew over the last two decades because of concerns about the environmental effects of conventional agricultural practices (Knowler & Bradshaw, 2007). CA is 'knowledge-intensive' because its proper application requires understanding the complexity of biological systems (Derpsch, 2008; Kassam et al., 2009). Its success depends mainly on the smallholder farmer's decision-making capacity instead of the technology itself. This is because CA-based systems require more biological activities and management than conventional systems to prevent the proliferation of new weeds and pests (Ekboir et al., 2002).

Scientific evidence shows that CA improves soil water conservation and soil quality (Li et al., 2011). Permanent soil cover increases available soil water by reducing evaporation and water overflow and promoting better rainwater retention (Franzluebbers, 2002; Huang et al., 2008, 2014; Lampurlanés & Cantero-Martínez, 2006). Decreasing water run-off also prevents water erosion and increases the chance for water to infiltrate the soil (Li et al., 2011; Potter et al., 1995). Compared with conventional agriculture, CA reduces soil compaction and enriches organic matter and soil carbon (Chan et al., 2002; Moreno et al., 2006). In other words, CA improves the productive potential of soils through enhanced interaction among physical, chemical, biological and hydrological factors (Kassam et al., 2009). Hence, it enhances the resilience of agricultural production systems against drought (Huang et al., 2008).

In general, farmers that adopt CA are expected to be more efficient at using agricultural resources than traditional farmers. This is because the former aims to minimise external input use through integrated agricultural systems management (García-Torres et al., 2010; Knowler & Bradshaw, 2007). Solís et al. (2007) did a cross-sectional analysis applying a switching regression approach (SRA) and concluded that farmers with higher levels of CA technology adoption had higher TE. On the contrary, Oduol et al. (2011) studied the impact of soil and water conservation technologies on TE in Uganda, Rwanda and DRC. They concluded that there is a significant negative relationship between TE and these technologies. Krishna and Veettil (2014) studied the impact of zero tillage on productivity and TE in the EGP and concluded that it increases wheat farmers' productivity by 5% and TE only by 1%. Ndlovu et al. (2014) analysed a 3-year panel dataset of Zimbabwean maize farmers and concluded that CA does not affect TE but increases farmer productivity by 39%. Finally, Chan et al. (2017) used data envelopment analysis (DEA) to explain the variations in efficiency among Indian maize farmers practising minimum tillage. They concluded that minimum tillage increases farmers' TE by at least 10% and their productivity by 60–70%. Therefore, it can be concluded that the relationship between CA and TE is still controversial.

As mentioned before, most of these studies failed to correct selection bias from observed and unobserved variables and to account for technology differences across groups. Therefore, an approach for addressing these issues that is adaptable to the nonlinear nature of the SPF is required (Bravo-Ureta et al., 2012; Greene, 2010; Villano et al., 2014). The approach is described in Section 3.

2.2 | CA in the Eastern Gangetic Plains

The Eastern Gangetic Plains (EGP) of South Asia comprises southern Nepal, north-eastern India and Northern Bangladesh and is a region with one of the highest concentration of rural population living under poverty in the world (Ericksen et al., 2011). Earlier research indicates that the agricultural systems in the EGP have reached a plateau in terms of overall productivity (Prasad, 2005) and exhibit low farm productivity and high yield variability, undermining a reliable food security foundation (Cornish et al., 2011). All these can be attributed to the progressive deterioration of natural resources due to intensive tillage and mismanagement of farming inputs (Jat et al., 2021).

CA emerged in South Asia as an alternative to intensive tillage (Chaudhary et al., 2022). Zero-till practices first arrived in the Western Indo-Gangetic Plains (WGP) in the late 80s as an alternative to the labour-intensive bed planting preparation practices (Hobbs et al., 2017).

The introduction of CA aimed to address the issue of delayed wheat planting and decreasing yield trends. Since its introduction, further developments to promote and foster its adoption have been carried out (Hobbs et al., 2017). However, the area under CA in South Asia remains relatively low compared with other regions with similar climatic conditions (Somasundaram et al., 2020).

Over the last decade, CA has been promoted as a climate-smart agriculture practice as it requires advanced water and nutrient management (Sidhu et al., 2019). While the majority of studies examining CA in the Indo-Gangetic Plains focus on the WGP, recent research conducted in the EGP suggests that CA plays a significant role in enhancing crop productivity growth, resource use efficiency and soil and water quality and reduces costs in comparison with non-CA farmers (Dixon et al., 2020; Gathala et al., 2011; Haque et al., 2016; Hossen et al., 2018; Islam et al., 2019). For example, Islam et al. (2019) concluded that farmers that partially adopted CA reported higher yields than conventional tillage farmers. Gathala et al. (2020) also reported higher yields for farmers transitioning to adopt CA fully. Likewise, Keil et al. (2020) suggested that zero tillage increases wheat yield compared with conventional tillage in Bihar.

While many studies found that CA increases farmers' productivity, little is known about the components of productivity gains from the adoption of the technology.

3 | ANALYTICAL FRAMEWORK

3.1 | Productivity and technical efficiency analysis

We follow the approach proposed by Villano et al. (2014) to address TE analysis correcting for biases coming from observables and unobservable characteristics and accounting for technology differences across groups. This approach combines the methods proposed by Bravo-Ureta et al. (2012) with a meta-frontier analysis. This requires propensity score matching (PSM) to account for self-selection bias from observable time-invariant characteristics and create comparable counterfactual groups of CA adopters and nonadopters. We then use the method developed by Greene (2010) to calculate the SPFs to measure TE and productivity with correction for sample selection bias coming from unobservable variables. We followed the method developed by Huang et al. (2014) to calculate a meta-frontier to generate technology gap ratios (TGRs) for CA and non-CA farmers. Statistical tests such as the generalised likelihood ratio test (GLRT) were then used to find the most appropriate model and to investigate whether adopters and nonadopters shared the same technology set.

3.1.1 | Propensity score matching

We use PSM to create a covariate-balanced dataset from our original sample to control for biases arising from observed characteristics. PSM has been widely applied in agricultural economics research to study technology adoption and impact evaluation accounting for self-selection bias from observable characteristics (e.g. Becerril & Abdulai, 2010; Mendola, 2007).

We use PSM to address the bias from observable variables (e.g. income, level of education and gender) and create a counterfactual group. This technique makes it possible to match CA farmers with non-CA farmers based on observed and time-invariant characteristics, creating two groups that are as identical as possible with only one exception: the adoption of CA.

To do so, we estimate a binary choice model (probit model) and use it to create propensity scores based on a set of observable characteristics (X); the propensity score for a farmer i is the probability p_i that the farmer adopts CA (is 'treated' or $T_i = 1$) and is defined in Equation (1) (Becker & Ichino, 2002).

$$p_i = p(X_i) = prob[T_i = 1|X_i] \tag{1}$$

The propensity scores are then used to match CA and non-CA farmers based on a 'common support' condition; that is, CA farmers with propensity scores outside the range of the non-CA farmers are considered as observably different or noncomparable and not considered in further analysis (Caliendo & Kopeinig, 2008).

Once the match is done, it is important to check the 'balancing hypothesis', ensuring that adopters' and nonadopters' average propensity scores are in the same range and have similar or same averages (Becker & Ichino, 2002). Once we have our new balanced sample, and assuming there is no unobserved bias, the actual impact of the adoption can be measured by calculating the average treatment effect on the treated (ATT), which represents the average effect of adoption (Winters et al., 2010):

$$\text{ATT} = E(Y_1|D = 1) - E(Y_0|D = 0) \tag{2}$$

where Y_1 and Y_0 represent the average values of the indicator (e.g. production per hectare or TE) for CA and non-CA farmers, respectively, and D is a dummy with a value of 1 for CA farmers.

3.1.2 | Stochastic production frontier with correction for sample selection

Stochastic production frontier (SPF) analysis has been used to analyse TE across different farming systems (e.g. see Bravo-Ureta and Rieger (1991) for English dairy farm efficiency; Rodriguez Sperat et al. (2017) for the Argentine dairy goat industry). It has also been used to study and compare farmer efficiency under different technology uses. Recent examples include Carrer et al. (2022) for comparing adopters and nonadopters of precision agriculture technologies and Ndlovu et al. (2014) for comparing between farms under CA and traditional tillage.

The standard stochastic frontier model is specified as:

$$Y_{jit} = f_t^j(X_{jit})e^{V_{jit} - U_{jit}}, \quad j = 1, \ldots, N; \quad i = 1, 2, \ldots, N; \quad t = 1, 2, \ldots, T \tag{3}$$

where Y_{jit} and X_{jit} represent, respectively, the output and input vectors for period t of the i-th farm in the j-th group. V_{jit} is the random noise term, and it is assumed to have a normal distribution $N \sim (0, \sigma_v^2)$; and U_{jit} represents the one-sided inefficiency term and is assumed to have a half-normal distribution $u \sim N(u, \sigma_u^2)$. Both V_{jit} and U_{jit} are assumed to be independent and identically distributed. Then, a farm's TE can be calculated as:

$$\text{TE}_{it}^j = \frac{Y_{jit}}{f_t^j(X_{jit})e^{-V_{jit}}} = e^{-U_{jit}} \tag{4}$$

The model in Equation (3) has two major shortcomings. First, it assumes there are no unobserved heterogeneities (Greene, 2010); and second, it puts farmers that belong to different groups (CA and non-CA) under the same technology umbrella (Orea & Kumbhakar, 2004). Nonobserved variables may affect estimates. For example, in South Asia, there exists a gender gap that prevents women from accessing new technologies. Moreover, as CA was introduced only recently (3 years before the data collection), nonexposure bias is a potential issue (Diagne & Demont, 2007). Additional sources of nonobserved biases include differences in farm biophysical characteristics, degree of risk aversion and farmer expectations.

To deal with bias from unobservables, we follow the approach developed by Greene (2010). This approach suggests that the unobservable part of the self-selection bias model is correlated with the statistical noise part of the composed error in the stochastic frontier model. This framework is an extension of the framework proposed by Heckman (1979) for linear regression models. Greene (2010) approach can be mathematically described as follows:

$$\text{Sample selection model: } d_i = 1\left[\alpha' z_i + w_i > 0\right], \quad w_i \sim N(0,1) \tag{5}$$

$$\text{Stochastic frontier model: } y_i = \beta' x_i + \varepsilon_i, \qquad \varepsilon_i = v_i - u_i \tag{6}$$

$$u_i = \left|\sigma_u U_i\right| = \sigma_u \left|U_i\right| \text{ where } U_i \sim N(0,1)$$

$$v_i = \sigma_v V_i \text{ where } V_i \sim N(0,1)$$

$$\left(w_i, v_i\right) \sim N_2\left[(0,0), \left(1, \rho\sigma_v, \sigma^2{}_v\right)\right]$$

where d_i is a binary variable that is equal to 1 for the group of farmers (CA or non-CA) for whom the selection model is estimated for; z_i is a vector of explanatory variables included in the sample selection; w_i is the unobservable error term correlated with v_i; y_i is log of output; x_i is the vector of (logged) inputs; and α and β are parameters to be estimated using simulated maximum likelihood estimation (SMLE). The coefficient ρ measures the correlation between the error term in the selection model and the noise term in the frontier model; a statistically significant ρ estimate signifies the existence of self-selection bias due to unobservable variables that influence both participation and production outcomes.

3.1.3 | Stochastic meta-frontier

The solutions specified above do not allow for a direct comparison of the TE between CA farmers and non-CA farmers because efficiency estimates are calculated with respect to separate group frontiers (González-Flores et al., 2014). To address this problem, we follow the approach to the estimation of stochastic meta-frontier (SMF) production functions proposed by Huang et al. (2014). The meta-frontier production function $f_t^M\left(X_{jit}\right)$ envelops both CA and non-CA group frontiers $f_t^j\left(X_{jit}\right)$. Huang et al.'s (2014) method is a two-step approach that requires first estimating the specific group stochastic frontiers and then pooling the output predictions from each group frontier and the corresponding input data to estimate the SMF. Then, the meta-frontier can be defined as:

$$\ln\widehat{f}^{\,j}_t\left(X_{jit}\right) = \ln f_t^M + V_{jit}^M - U_{jit}^M, \quad \forall i, t, j = 1, 2, \ \dots, J \tag{7}$$

where $\ln\widehat{f}^{\,j}_t\left(X_{jit}\right)$ is the estimate of each group-specific frontier from the first step in Equation (3) or Equation (6) in the presence of selection bias. Since the estimates $\ln\widehat{f}^{\,j}_t\left(X_{jit}\right)$ are group-specific, the regression is estimated two times, one for each group (CA and non-CA farmers). These estimates from each group are then pooled together to estimate Equation (7). Technology gap ratio (TGR) and the meta-frontier technical efficiency (MTE) are defined as:

$$\text{TGR}_{it}^j = \frac{f_t^j\left(X_{jit}\right)}{f_t^M\left(X_{jit}\right)} \tag{8}$$

$$\text{MTE}_{jit} = \text{TGR}_{it}^j * \text{TE}_{it}^j \tag{9}$$

4 | DATA AND EMPIRICAL MODEL

The data for this paper come from a socio-economic farm household survey conducted in 2018 by researchers participating in the 'Sustainable and Resilient Farming Systems Intensification in the Eastern Gangetic Plains' (SRFSI) project (Rola-Rubzen et al., 2019). The SRFSI project aims to increase productivity and improve climate change resiliency of farmers in the EGP by trailing CA across farmers from north-west Bangladesh, the Indian states of Bihar and Western Bengal and the Nepal Terai. Since many farmers in the EGP have reported reluctance to adopt the full technology set (Islam et al., 2019), the SRFSI project adopted a gradual approach, with farmers having various levels of adoption and many adopting the technology only partially in the initial stages. We use data of 220 farm households located in different areas of Rangpur (Bangladesh) that produced maize during the rabi season in 2017. Among the 220 farmers, 123 were either SRFSI core participants or SRFSI scale-out farmers, while the remaining 97 were non-SRFSI farmers. Both SRFSI core and SRFSI scale-out participants have fully or partially adopted CA, while non-SRFSI farmers have adopted none. In other words, for this paper, we consider CA farmers to be those farmers that have adopted at least one CA practice. The main difference between SRFSI core participants and SRFSI scale-out farmers is that the former have received technical assistance from scientists and technicians and some free inputs. In contrast, the latter have fully or partially adopted CA because of the spillover effects.

As mentioned before, we follow the approach developed by Bravo-Ureta et al. (2012), which combines PSM with the methodology proposed by Greene (2010) to get unbiased estimates of the coefficients of the production function and calculate farmers' TE. The variables used for PSM and the model specifications are based on literature review and data availability. Table 1 shows the variables used for the empirical analysis.

We used the Epanechnikov kernel matching method with a calliper of 0.04, imposing the common support condition and allowing for controls to be reused. We chose this method because it relies mainly on the sample size; because we allow for controls to be reused, we use a predefined neighbourhood (calliper) to prevent an increase in the bias if inferior matches are done (Cameron & Trivedi, 2005). While PSM does not control for all bias coming from observed variables, it usually yields acceptable results (Imbens & Wooldridge, 2009).

The matched sample contains 196 observations, composed of 99 CA farmers and 97 non-CA farmers. A t-test was performed to compare the weighted average values of the observed time-invariant characteristics between CA farmers and non-CA farmers. It suggested that the 'balancing hypothesis' has been satisfied for all covariates except for AGE. The full PSM output is included in supplementary files to this article (Appendix S1).

Table 2 shows the summary statistics for the matched and unmatched samples and test results from equality of mean values across CA and non-CA farmer subsamples. In general, both farmer groups show similar average values for the age of the household head, years of farming experience and ownership of land. However, CA farmers have significantly higher average values for education, income from sources other than maize farming and the proportion of female household heads. The mean value of total land under irrigation (IRRLAND) differs significantly across the groups. The relationship between these variables and CA technology adoption will be discussed in detail in a subsequent section. On the contrary, non-CA farmers use considerably more land, labour and other inputs (EXPENSE) to obtain, on average, similar values of total production. These results imply that CA farmers have greater input productivity.

Finally, the fact that the test on the means values indicates significant differences for EDUCATION, IRRLAND, GENDER and INCOME between matched and unmatched data suggests that the PSM matching quality can be improved. It is possible that by employing a different matching method, we could come up with two samples that are more similar across

TABLE 1 Definition of variables used in the propensity score matching (PSM) and stochastic production function (SPF) models.

Variable	Parameter	Unit	Definition
SPF Model			
PROD		kilogram	Output: Total maize produced during the rabi season
LAND	α_1	hectare	Total land allocated to maize production during the rabi season
LABOUR	α_2	hours	Total labour used in maize farming expressed in male adult equivalent unit
EXPENSE	α_3	Bangladeshi taka	Farm production expenditures coming from fertiliser, irrigation, herbicide, insecticide, fungicide, micronutrients and seed
CA	α_{CA}	dummy	1 if farmer is a CA farmer, 0 otherwise
Probit Model			
AGE	β_1	years	Age of the household head
EXPERIENCE	β_2	years	Farming experience of the household head
EDUCATION	β_3	years	Years of formal education of the household head
IRRLAND	β_4	hectare	Total land under irrigation
OWNLAND	β_5	dummy	1 if farmer owns the land, 0 otherwise
GENDER	β_6	dummy	1 if household head is male, 0 otherwise
INCOME	β_7	Bangladeshi taka	Total income from sources other than maize farming

Note: Bangladeshi taka 85.08 BDT ≅ 1 USD (Google Analytics, 2021).

TABLE 2 Descriptive statistics of the matched and unmatched samples.

	Pooled		**CA† farmers**		**Non-CA farmers**		
Variable	**Mean**	**SD‡**	**Mean**	**SD‡**	**Mean**	**SD‡**	***T*-test**
Unmatched data							
PROD	1591	307	1595	329	1586	277	−0.220
LAND	0.161	0.037	0.153	0.034	0.170	0.034	3.349***
LABOUR	222	58	210	47	237	67	3.323***
EXPENSE	4795	1357	4630	1455	5004	1197	2.092**
AGE	41.932	9.727	41.902	9.207	41.969	10.397	0.049
EXPERIENCE	16.391	7.749	16.732	7.714	15.959	7.811	−0.733
EDUCATION	7.404	4.069	8.504	3.260	6.010	4.556	−4.549***
IRRLAND	0.563	0.333	0.601	0.357	0.515	0.295	−1.957*
OWNLAND	0.990	0.095	0.992	0.090	0.989	0.101	−0.166
GENDER	0.864	0.343	0.772	0.421	0.979	0.143	5.094***
INCOME	46,573	37,444	51,207	41,767	40,698	30,324	−2.160**
Observations	220		123		97		
Matched data							
PROD	1588	321	1590	360	1586	277	−0.0870
LAND	0.161	0.038	0.152	0.037	0.170	0.034	3.199***
LABOUR	222	58	208	43	237	67	3.613***
EXPENSE	4837	1423	4673	1604	5004	1197	1.636**
AGE	42.326	0.209	42.677	9.619	41.969	10.397	−0.495
EXPERIENCE	16.75	7.981	17.525	8.108	15.959	7.811	−1.377
EDUCATION	7.270	4.151	8.505	3.293	6.010	4.556	−4.399***
IRRLAND	0.568	0.328	0.619	0.352	0.515	0.295	−2.255***
OWNLAND	0.989	0.101	0.989	0.100	0.989	0.101	−0.014
GENDER	0.954	0.209	0.929	0.258	0.979	0.143	1.678**
INCOME	46,707	34,323	52,595	37,049	40,698		−2.457***
Observations	196		99		97		

Note: ***, ** and * means between CA adopters and nonadopters are significantly different at the 1%, 5% and 10% levels, respectively. † and ‡ mean 'conservation agriculture' and 'standard deviation', respectively.

these four covariates. However, that would be achieved at the cost of a reduced sample size and less precise estimates from the analysis.

Once the CA and non-CA farmers have been matched, we estimated the SPF with correction for sample selection. To do so, we defined the sample selection model that predicts the probability of the ith farmer's decision to adopt CA as the following probit model:

$$\mathrm{CA}_i = \alpha_0 + \sum_{1}^{n} \alpha_{ij} Z_{ij} + w_i \tag{10}$$

where CA is a dichotomous variable equal to 1 if the ith farmer adopts CA, Z is a vector of exogenous variables that explain adoption, α is the unknown parameter vector to be estimated, and w is a disturbance term distributed as $N \sim (0,1)$.

The two functional forms we consider for our production functions are Cobb–Douglas (CD) and translog (TL), as these are the two most commonly used functional forms in efficiency studies (Bravo-Ureta et al., 2007). However, a maximum likelihood ratio test suggested the CD functional form is not adequate to represent the production technology. Thus, the discussion in this paper will focus on the TL functional form and related results. A TL SPF can be defined as:

$$y_i = \alpha_0 + \sum_{j=1}^{n} \alpha_j x_{ij} + \frac{1}{2} \sum_{j=1}^{n} \sum_{k=1}^{n} \alpha_{jk} x_{ij} x_{ik} + v_i - u_i \tag{11}$$

where y_i represents the log of the output of the ith farmer; x_{ij} represents the log of the quantity of the jth-input for the ith farmer; α's represents the unknown parameter to be estimated; and v and u are the elements of the composed error term, ε. The output in our model is total kilogram of maize produced during the rabi season in 2017. The Rabi season is one of the main agricultural seasons in several South Asian countries. It typically goes from November to mid-March. It is a dry season, and most crops depend on the rainfall received and stored in the soil during the preceding monsoon season. The inputs are total land allocated to maize production during the rabi season 2017 (LAND) expressed in hectares; total labour used in maize farming (LABOUR) expressed in male adult equivalent units; and production expenditures on fertiliser, irrigation, herbicide, insecticide, fungicide, micronutrients and seed (EXPENSE) expressed in Bangladeshi taka (85.08 BDT $\cong$ 1 USD). All models have been estimated using NLOGIT 6S and StataSE17.

5 | RESULTS AND DISCUSSION

5.1 | Conservation agriculture technology adoption

In this section, we present the probit sample selection model results and then relate our findings to previous studies mentioned in Section 2. The probit model results are presented in Table 3, and a confusion matrix for the probit model is included in supplementary files to this article (Appendix S2). The chi-squared statistic is 50.638 (significant at 1%), implying the joint significance of the parameters for the CA adoption determinants. The variables EXPERIENCE, EDUCATION, IRRLAND and GENDER are found to influence the decision to adopt CA technology significantly. Another potential explanator−access to credit−could not be included because none of the farmers in the sample has access to it. Membership in farmer groups was also not included in the analysis because it was almost synonymous with the variable being explained (CA adoption).

TABLE 3 Parameter estimates of probit selection model using matched data.

Variable	Coefficient (SE)	Marginal effect (SE)
CONSTANT	−0.596 (1.107)	
AGE	−0.003 (0.015)	−0.001 (0.005)
EXPERIENCE	0.040 (0.019)**	0.013 (0.006)**
EDUCATION	0.148 (0.029)***	0.048 (0.008)***
IRRLAND	0.903 (0.327)***	0.290 (0.099)***
OWNLAND	−0.661 (0.958)	−0.212 (0.307)
GENDER	−2.403 (0.557)***	−0.772 (0.154)***
INCOME (millions)	5.274 (3.229)	1.695 (1.020)*
Log-likelihood function	−110.528	
Chi-squared test statistic	50.6379***	
Number of observations	196	

Note: ***, ** and * means significant at the 1%, 5%, and 10% levels, respectively.

EXPERIENCE significantly and positively affects CA technology adoption, supporting the findings by Rahm and Huffman (1984) and Clay et al. (1998). This is because more experienced farmers tend to think positively about investment and the sustainable use of resources (Clay et al., 1998). However, Rahm and Huffman (1984) suggested experience can have an ambiguous effect on CA technology adoption depending on the planning horizon. As expected, EDUCATION is significant in explaining the adoption of CA, supporting findings by other researchers on different agricultural technologies (Mignouna et al., 2011; Rahm & Huffman, 1984; Tsegaye et al., 2008, 2017). Because CA is a knowledge-intensive technology (Ekboir et al., 2002), there is a link between knowledge and its adoption (Knowler & Bradshaw, 2007).

We consider the variable IRRLAND (total irrigated land) to be a proxy for total land under agriculture during the rabi (dry) season. This is because most rabi crops in Bangladesh are cultivated under irrigation. The variable IRRLAND (total irrigated land) has a positive and significant effect, consistent with other findings (Ahmed & Bagchi, 2004; Kasenge, 1998; Villano et al., 2014). Farmers that own more extensive land can give up a portion of their land to try new technologies (Uaiene, 2011), and by doing so, they reduce the risk of technology failure (Villano et al., 2014). Additionally, agriculture under CA requires less water than agriculture under conventional tillage. Therefore, farmers with less land under irrigation tend to allocate it to conventionally produced crops (Akter et al., 2021). The variable OWNLAND is statistically insignificant because most farmers in the sample are landowners, as shown in Table 2.

In general, the variable INCOME plays an important role in agricultural technology adoption (Fuglie, 1999; Gould et al., 1989; Somda et al., 2002) as off-farm income is a source of financial assets that can be used to purchase inputs and new technology (Diiro, 2013). Our results show that INCOME appears to have a positive but not significant effect. AGE is also found to be insignificant in explaining CA adoption.

The coefficient of GENDER is negative and significant at the 1% level, implying that female farmers had a greater probability of adopting CA technology in Rangpur. Farnworth et al. (2016) suggested that the current literature is insufficient regarding the relationship between gender and CA adoption. However, our results show that CA is a female-friendly technology in Rangpur, which is consistent with what our research team observed in the field. This can perhaps be attributed primarily to male-labour outmigration from the EGP and the nature of the CA technology. Migration means less male labour available for agriculture, and as a consequence, females are likely to take more responsibility for agriculture in addition to their household chores (Darbas et al., 2020; Tamang et al., 2014). On the contrary, CA makes up for the labour shortage because it requires less labour for land preparation and crop establishment, as these are replaced by mechanisation (Gathala et al., 2015, 2020; Sinha et al., 2019).

Since women have less access to off-farm income opportunities, they are commonly paid less, and their off-farm income opportunities are less secure than men's (FAO, 2011; Lai et al., 2012). Our results imply that CA can be included in a broader strategy to address gender inequality in rural areas in developing countries.

5.2 | Stochastic frontier models and production functions

As mentioned earlier, the main aim of this study is to analyse potential differences in TE between CA farmers and non-CA farmers, controlling for bias from both observed and unobserved factors. In Table 4, we report estimates for both the matched sample models with and without correcting for selection bias. We present these results to compare the estimates between our biased and unbiased models and examine the technology differences between adopters and nonadopters. All variables have been normalised by their sample mean values. Thus,

TABLE 4 Parameter estimates of the conventional and sample selection SPF models: matched sample.

			Conventional (CC) SPF				Sample selection (SS) SPF			
	Pooled		CA†		Non-CA†		CA†		Non-CA†	
Variable	Coeff.‡	SE.§	Coeff.‡	SE.§	Coeff.‡	SE.§	Coeff.‡	SE.§	Coeff.‡	SE.§
Constant	7.471***	0.013	7.482***	0.007	7.490***	0.017	7.468***	0.019	7.443***	0.036
LAND	0.282***	0.047	0.379***	0.058	0.351***	0.065	0.434***	0.084	0.371***	0.086
LABOUR	−0.1667*	0.087	0.327***	0.053	−0.147	0.116	0.346***	0.061	−0.145	0.114
EXPENSE	0.373***	0.075	0.336***	0.048	0.334***	0.083	0.335***	0.081	0.221**	0.091
$LAND^2$	−0.314	0.331	−0.862**	0.373	−0.260	0.491	−0.964*	0.53	−0.680	0.525
$LABOUR^2$	2.104***	0.458	0.587	0.373	2.585***	0.625	0.621	0.452	2.830***	0.525
$EXPENSE^2$	1.546***	0.583	0.954**	0.479	1.037	0.638	0.385	0.812	0.786	0.917
LAND*LABOUR	1.081***	0.340	−0.261	0.317	1.859***	0.445	−0.213	0.481	1.908***	0.539
LAND*EXPENSE	−0.899***	0.308	−0.416	0.331	−1.486***	0.346	−0.089	0.518	−1.370***	0.503
LABOUR*EXPENSE	−1.938***	0.507	−0.238	0.386	−2.830***	0.631	−0.181	0.526	−2.884***	0.667
CA†	0.039***	0.016								
CA*LAND	0.274***									
CA*LABOUR	0.561***	0.129								
CA*EXPENSE	−0.099	0.095								
Lambda (λ)	5.661***	0.872	3.651***	0.849	4.821***	1.536				
Sigma (σ)	0.184***	0.001	0.094***	0.001	0.211***	0.002				
Sigma-u (σ_u)							0.078***	0.011	0.178***	0.026
Sigma-v (σ_v)							0.034***	0.009	0.082***	0.027
Rho-w,v ($\rho_{(w,v)}$)							0.373	0.682	0.799*	0.411
Log-Likelihood	165.080		143.471		66.535		87.350		12.79	
N	196		99		97		99		97	

Note: ***, ** and * means significant at the 1%, 5% and 10% levels, respectively. †, ‡ and § means 'conservation agriculture', 'coefficient' and 'standard error', respectively.

the partial production elasticities at mean values are defined by the first-order coefficients for the average producer (Coelli et al., 2003).

The pooled model suggests a significant difference between the two groups (CA is significant at 1%). These results are supported by a likelihood ratio test result (−89.852,[1] p-value = 0.000), rejecting the null hypothesis that there is no difference between the pooled frontier model and the two group frontier models. That is, the production frontier parameters are not the same for adopters and nonadopters. Therefore, it is necessary first to estimate separate group frontiers and then estimate the meta-frontier to compare TE across groups (Huang et al., 2014).

For the sample selection models (last four columns in Table 4), the significance test results on ρ show that the standard stochastic frontier model is rejected because there are selection biases arising from unobservable characteristics in the case of nonadopters, but this does not apply to the case of adopters. This is similar to the interpretation provided by Greene (2010) in his analysis of data from the World Health Organization (WHO). These results justify the use of the framework proposed by Greene (2010) to estimate separate frontiers for the CA and non-CA groups. This suggests that the standard frontier model for non-CA farmers leads to biased TE estimates (Bravo-Ureta et al., 2012; Villano et al., 2014). Thus, for the estimation of the meta-frontier and further analysis, we use the sample selection models for both CA and non-CA farmers. The sample selection stochastic frontier is also used for adopters to improve the observable bias control as the unobservables are conditional on the observables included in the selection model (Equation (5)).

Examining the estimated production frontier parameters, LAND has a relatively large first-order (linear) coefficient and is statistically significant in both the CA and non-CA frontiers. LABOUR shows a positive and significant linear coefficient for CA farmers but not for non-CA farmers. On the contrary, squared and interaction terms for LABOUR are significant for non-CA farmers. The variable EXPENDITURE has a positive and significant linear coefficient for CA and non-CA farmers. The interaction between this variable and LAND or LABOUR is significant but negative.

Although the pooled model is biased, it gives the first insight that farmers who have adopted CA increase their output by 3.9%. These results are consistent with those reported by Ndlovu et al. (2014) and Chan et al. (2017), who found that the adoption of CA increases maize production by 39% and 60–70%, respectively. The gap between estimates might be because most CA farmers participating in the SRFSI project in Rangpur are still in the transition phase. Moreover, the interaction terms in the pooled model suggest that CA has a differential effect on labour and land productivity. Finally, the returns to scale (the sum of all partial production elasticities from the sample selection models) for CA farmers is equal to 1.165 and for non-CA farmers is equal to 0.578, which implies that input use is more productive with CA farmers than with non-CA farmers who have a technology characterised by decreasing returns to scale (DRTS). The conventional models also suggest that input use is more productive with CA farmers than with non-CA farmers. This interpretation is supported by previous studies in the EGP that concluded that CA-based sustainable intensification leads to better productivity (Dixon et al., 2020; Gathala et al., 2020). Several potential reasons may explain why CA farmers operate under IRTS and non-CA farmers under DRTS. CA farmers are still familiarising themselves with the new technology and still have room for improvement and are still learning about CA practices. As a result, their operations could still be in the discovery phase and may be suboptimal. There could also be other reasons why their operations appear suboptimal, such as lower input use (Table 2), higher dependency on herbicides and zero tillage machinery of CA farmers (Islam et al., 2016; Wall, 2007) and restricted access to CA machinery and herbicides in Rangpur (Islam et al., 2016). These are constraints that would prevent farmers from optimising the scale of their operations. The results for non-CA farmers reflect that labour and land productivity decreases at higher scales, a typical characteristic of subsistence

[1] $\text{LR} = 2 * \left(\left(\text{Ln} L_{\text{CA}} + \text{Ln} L_{\text{non-CA}} \right) - \text{Ln}\, L_{\text{pooled}} \right)$

farming. One possible explanation for this occurrence is that non-CA farmers lack the necessary labour capacity to manage larger farms, effectively. Another potential explanation is that expanded land holdings may be associated with lower average land quality due to factors such as soil type, salinity, slope and other factors that reduce land productivity. However, it should be noted that we have not measured the quality of labour or land to fully validate our interpretation.

5.2.1 | Maize farmers' technical efficiency and productivity in Northern Bangladesh

The lambda for the stochastic frontier (i.e. the ratio of the standard deviation values for the inefficiency variable and the symmetric error term) is significant at the 1% level for both CA and non-CA farmers. This result implies that farmers' inefficiency is relatively important in explaining the deviation of actual observed output from their relevant estimated potential output.

As mentioned in the previous section, the likelihood ratio test suggested the existence of a potential production technology gap, which justifies the estimation of the meta-frontier production function among farmers in Rangpur. Our parameter estimates for the SMF based on Huang et al. (2014) are presented in Table 5. The frontier is used to calculate the MTE and TGR and to make a comparison between CA farmers and non-CA farmers.

Table 6 presents the sample statistics of various efficiency scores for the two groups of farmers. The group-specific TE scores show a TE level of 0.94 for CA farmers and a TE level of 0.87 for non-CA farmers. CA farmers are more technically efficient with respect to their specific group than non-CA farmers. The TGR scores show that CA farmers also seem to be more efficient in adopting the best available agricultural technology. The TGR score for CA farmers is 0.94, while for non-CA farmers is 0.91. Overall, CA farmers are more technically efficient than non-CA farmers, as shown by the MTE estimates, and our results are consistent with those reported by Abdulai and Abdulai (2018) and Aravindakshan et al. (2018). As in the study on Taiwanese hotel chains by Huang et al. (2014), TE slightly outweighs TGR in explaining MTE.

TABLE 5 Parameter estimates of the meta-frontier.

Variables	Coefficient	SE
Constant	7.503	0.006
LAND	0.358***	0.029
LABOUR	0.091***	0.025
EXPENSE	0.386***	0.035
$LAND^2$	−1.008***	0.196
$LABOUR^2$	1.789***	0.172
$EXPENSE^2$	3.281***	0.315
LAND*LABOUR	0.4351***	0.139
LAND*EXPENSE	−1.107***	0.204
LABOUR*EXPENSE	−2.171***	0.239
Lambda (λ)	6.237***	0.011
Sigma (σ)	0.116***	0.008
Log-Likelihood	256.424	
N	196	

Note: *** means significant at the 1% level.

TABLE 6 Summary statistics of Rangpur maize farmers' efficiency measures.

	All farmers		CA farmers		Non-CA farmers		
Variable	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	***T*-test**
TGR	0.92	0.06	0.94	0.04	0.91	0.08	−3.67***
TE (SS)	0.89	0.06	0.94	0.04	0.87	0.08	−8.08***
MTE	0.82	0.09	0.88	0.05	0.79	0.09	−8.84***

Note: *** means that CA adopters and nonadopters are significantly different at the 1% level.

These results suggest that the primary source of inefficiency is related to farmers not generating the most output possible for their practices rather than adopting CA technology.

The results presented in Table 6 suggest that CA adoption increased average efficiency by 9%. This is because efficiency is associated with the managerial capacity of the farmer (Bravo-Ureta et al., 2007), and as CA is a knowledge-intensive technology (Ekboir et al., 2002), the success of this technology depends mainly on farmers' management rather than the amount of inputs applied. It could also be because farmers that adopted CA are more efficient at using water, energy and labour (Gathala et al., 2020; Sinha et al., 2019; Tessema et al., 2018), which is consistent with what we showed in Table 2. Moreover, CA aims to minimise external input use through an integrated management perspective of the agricultural systems, making the use of agricultural resources more efficient than in traditional agriculture (García-Torres et al., 2010; Knowler & Bradshaw, 2007). Our findings are consistent with Chan et al. (2017), who concluded that maize farmers that adopt CA have higher TE than those who used conventional tillage, but not with Ndlovu et al. (2014), who reported that CA has no effect on maize farmers' TE.

Table 7 reports the average treatment effect on the treated (ATT) of the average observed and frontier yields with respect to farmers' own group frontiers. In other words, the latter is defined as the average expected yield if each farmer group increased their efficiency up to 100%. These results suggest that CA farmers increase their observed yield by 8% compared with non-CA farmers. Moreover, the results reported in Tables 6 and 7 indicate that CA farmers have a 6% average inefficiency; that is, farmers that have adopted CA have the potential to increase their actual yield of 10,462 kg/ha up to 11,129 kg/ha. The difference between the frontier and observed yields for the non-CA farmers' group is bigger (13%); that is, non-CA farmers have the potential to increase their actual average yield of 9630 kg/ha up to 10,963 kg/ha. These findings suggest that although Bangladesh has recently witnessed rapid yield and production growth (Rahman & Rahman, 2014), adopting CA can further increase maize productivity in the country.

The average frontier yield is not significantly different for CA and non-CA farmers. These results suggest that farmers that have adopted CA increased their productivity mainly due to managerial abilities. This is perhaps because many farmers are still in the trialling phase and learning about the technology. However, as some researchers have pointed out, the long-term effect of CA can be negative if farmers do not become full adopters (Corbeels et al., 2014; Govaerts et al., 2008; Rusinamhodzi et al., 2011). Zero tillage practices without mulching and crop rotation are reported to have a negative impact on crop production in the long run (Corbeels et al., 2014; Govaerts et al., 2008; Rusinamhodzi et al., 2011). Adopting no-tillage without adopting the other principles of CA results in soil erosion and compaction (Baudron et al., 2012), and mulching is a very important factor in CA (Corbeels et al., 2014). In other words, intensifying CA practices in Rangpur is a must in the coming years to further improve and strengthen food security by exploiting the synergies among the different elements of CA.

TABLE 7 Average observed and frontier yield for adopters and nonadopters.

	CA farmers	Non-CA farmers	Test of means
Observed yield (kg/ha)	10,462	9630	−3.51***
Frontier yield (kg/ha)	11,129	11,069	−0.16

Note: *** means significant at the 1% level.

6 | CONCLUSION

This study investigates the impact of CA technology on the TE of maize farmers in Rangpur, Bangladesh. We use an impact evaluation approach controlling for selection bias using a framework that is adaptable to the nonlinear nature of the stochastic frontier in analysing CA adoption and TE. Comparing the TE of CA and non-CA maize farmers in Bangladesh, we conclude that, first, CA increases farming TE and actual observed yield per hectare (productivity) after 3 years of adoption. Second, farmers that have adopted CA have lower input use and greater input productivity. Third, evaluated after 3 years of adoption, CA did not appear to have significantly increased farmers' frontier yields. Finally, women from Rangpur were more willing to participate in CA adoption than men, going against the conventional belief that women are less interested in new agricultural technology.

This research provides lessons for evidence-based policymaking that can also be relevant to other areas in the EGP. This is because Rangpur is the main maize-producing district in Bangladesh (Karim et al., 2010), and CA shows consistent effects across countries and crops in the EGP (Gathala et al., 2020; Islam et al., 2019; Rola-Rubzen et al., 2019), and there are similar demographic and environmental challenges across the region (Brown et al., 2020). First, our research suggests that CA could be included in a broader strategic plan to promote gender equality in the Indo-Gangetic Plains. This is because CA requires less labour than conventional agriculture and, hence, has the potential to help women reduce their overloaded daily activities, which have been compounded by male outmigration. Second, our results suggest that CA could improve food security rapidly by contributing to a greater food supply in the local market as it is a technology that can increase per-hectare production rapidly. Third, CA is likely to reduce production costs while increasing revenue; in other words, it is likely to increase farmers' profitability as CA farmers reported less input use to obtain more output than non-CA farmers. Fourth, since many farmers in this region are reluctant to change their traditional practices, empirical evidence of the benefits of CA, such as those included in this paper, can be used to provide more information to promote CA technology in food-insecure areas of Bangladesh.

Farmers from Rangpur who adopt CA technologies face two major challenges. First, the availability of tractor-mounted mechanical planters during production season still represents a major limitation to CA adoption (Islam et al., 2016). Second, the availability of herbicides is limited and farmers have little experience applying them to different crops (Islam et al., 2016); this challenge is more important to CA than non-CA farmers because the formers rely more on herbicides for weed control (Wall, 2007). Improvements to current subsidies and other support measures are needed to speed up the region's mechanisation (Brown et al., 2020). Similarly, subsidies and extension support programs will be necessary to promote the effective and enhanced use of agrochemicals among farmers and create more competitive markets for inputs in the long run.

Finally, it is useful to point out the limitations of this study. Our research has focussed on maize cropping systems in the rabi season and assessed the effects of CA 3 years after adoption. Furthermore, the farmers under observation are not full CA farmers. We recommend that future studies evaluate the impact of CA technology adoption on farmers' TE in more detail using data from different cropping systems and covering full-adoption cases, that is farmers that practise crop rotation and permanent soil cover in addition to zero tillage. Furthermore, given its potential for increasing yield in the long run and that 3 years of adoption can still be considered short run, future studies should assess the effects over extended time frames.

ACKNOWLEDGEMENTS

We acknowledge the Sustainable and Resilient Farming Systems Intensification in the Eastern Gangetic Plains (SRFSI) project (CSE/2011/077), funded by the Australian Centre for International Agricultural Research (ACIAR) and the Australian Government Department of Foreign Affairs and Trade (DFAT), for providing the survey data used in this paper. We are also grateful to CIMMYT, RDRS Bangladesh and the University of Western Australia. Open Access funding enabled and organized by Projekt DEAL.

FUNDING INFORMATION

This research was conducted under the Sustainable and Resilient Farming Systems Intensification in the Eastern Gangetic Plains (SRFSI) project (CSE/2011/077) funded by the Australian Centre for International Agricultural Research (ACIAR) and the Australian government Department of Foreign Affairs and Trade (DFAT). The contents and opinions expressed herein are those of the authors and do not necessarily reflect the views of ACIAR or DFAT.

DATA AVAILABILITY STATEMENT

Author elects to not share data.

ORCID

Bruno Paz https://orcid.org/0000-0002-5772-7054
Maria Fay Rola-Rubzen https://orcid.org/0000-0003-3367-6931

REFERENCES

Abdulai, A.-N. & Abdulai, A. (2018) Examining the impact of conservation agriculture on environmental efficiency among maize farmers in Zambia. *Environment and Development Economics*, 22(2), 177–201. Available from: https://doi.org/10.1017/S1355770X16000309

Ahmed, S. & Bagchi, K. (2004) Factors and constraints for adopting new agricultural technology in Assam with special reference to Nalbari district: An empirical study. *Journal of Contemporary Indian Policy*, 11(1), 359–376.

Akter, S., Gathala, M.K., Timsina, J., Islam, S., Rahman, M., Hassan, M.K. et al. (2021) Adoption of conservation agriculture-based tillage practices in the rice-maize systems in Bangladesh. *World Development Perspectives*, 21, 100297. Available from: https://doi.org/10.1016/j.wdp.2021.100297

Aravindakshan, S., Rossi, F., Amjath-Babu, T.S., Veettil, P.C. & Krupnik, T.J. (2018) Application of a bias-corrected meta-frontier approach and an endogenous switching regression to analyze the technical efficiency of conservation tillage for wheat in South Asia. *Journal of Productivity Analysis*, 49, 153–171. Available from: https://doi.org/10.1007/s11123-018-0525-y

Asadullah, M.N. & Rahman, S. (2009) Farm productivity and efficiency in rural Bangladesh: the role of education revisited. *Applied Economics*, 41(1), 17–33. Available from: https://doi.org/10.1080/00036840601019125

Baudron, F., Tittonell, P., Corbeels, M., Letourmy, P. & Giller, K.E. (2012) Comparative performance of conservation agriculture and current smallholder farming practices in semi-arid Zimbabwe. *Field Crops Research*, 132, 117–128. Available from: https://doi.org/10.1016/j.fcr.2011.09.008

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. Available from: 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. Available from: https://doi.org/10.1177/1536867X0200200403

Bravo-Ureta, B.E., Greene, W. & Solís, D. (2012) Technical efficiency analysis correcting for biases from observed and unobserved variables: an application to a natural resource management project. *Empirical Economics*, 43(1), 55–72. Available from: https://doi.org/10.1007/s00181-011-0491-y

Bravo-Ureta, B.E. & Rieger, L. (1991) Dairy farm efficiency measurement using stochastic Frontiers and neoclassical duality. *American Journal of Agricultural Economics*, 73(2), 421–428. Available from: https://doi.org/10.2307/1242726

Bravo-Ureta, B.E., Solís, D., López, M., Víctor, H., Maripani, J.F., Thiam, A. et al. (2007) Technical efficiency in farming: a meta-regression analysis. *Journal of Productivity Analysis*, 27(1), 57–72. Available from: https://doi.org/10.1007/s11123-006-0025-3

Brown, P.R., Darbas, T., Kishore, A., Rola-Rubzen, M.F., Murray-Prior, R., Anwar, M.M. et al. (2020) *Implications of conservation agriculture–based sustainable intensification technologies for scaling and policy: Synthesis of SRFSI phase 1 socioeconomic studies (2012–17)*. ACIAR Technical Report 93.

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

Cameron, A.C. & Trivedi, P.K. (2005) *Microeconometrics: Methods and applications*. Cambridge: Cambridge University Press.

Carrer, M.J., Filho, H.M.d.S., Vinholis, M.d.M.B. & Mozambani, C.I. (2022) Precision agriculture adoption and technical efficiency: An analysis of sugarcane farms in Brazil. *Technological Forecasting and Social Change*, 177, 121510. Available from: https://doi.org/10.1016/j.techfore.2022.121510

Chan, C., Sipes, B., Ayman, A., Zhang, X., LaPorte, P., Fernandes, F. et al. (2017) Efficiency of conservation agriculture production systems for smallholders in rain-fed uplands of India: a transformative approach to food security. *Land*, 6(3), 58. Available from: https://doi.org/10.3390/land6030058

Chan, K.Y., Heenan, D.P. & Oates, A. (2002) Soil carbon fractions and relationship to soil quality under different tillage and stubble management. *Soil and Tillage Research*, 63(3–4), 133–139. Available from: https://doi.org/10.1016/S0167-1987(01)00239-2

Chaudhary, A., Timsina, P., Suri, B., Karki, E., Sharma, A., Sharma, R. et al. (2022) Experiences with conservation agriculture in the eastern Gangetic Plains: farmer benefits, challenges, and strategies that frame the next steps for wider adoption. *Frontiers in Agronomy*, 3, 787896. Available from: https://doi.org/10.3389/fagro.2021.787896

Clay, D., Reardon, T. & Kangasniemi, J. (1998) Sustainable intensification in the highland tropics: Rwandan Farmers' Investments in land conservation and soil fertility. *Economic Development and Cultural Change*, 46(2), 351–377. Available from: https://doi.org/10.1086/452342

Coelli, T., Estache, A., Perelman, S. & Trujillo, L. (2003) *A primer on efficiency measurement for utilities and transport regulators*. Washington, DC: World Bank (WBI Development Studies).

Coelli, T.J., Rao, D.S.P., O'Donnell, C.J. & Battese, G.E. (2005) *An introduction to efficiency and productivity analysis*, 2nd edition. New York, NY: Springer.

Corbeels, M., Sakyi, R.K., Kühne, R.F. & Whitbread, A.M. (2014) *Meta-analysis of crop responses to conservation agriculture in sub-Saharan Africa: CGIAR Research Program on Climate Change, Agriculture and Food Security*. Available from: https://cgspace.cgiar.org/handle/10568/41933 [Accessed 27th September 2023].

Cornish, P.S., Wall, P.C., Singh, K.M. & Singh, S.S. (2011) *Food security and poverty reduction in the Eastern Gangetic Plains*. Available from: https://www.researchgate.net/profile/k-singh-12/publication/236179363_food_security_and_poverty_reduction_in_the_eastern_gangetic_plains/data/00b49516e8582b8496000000/final-e-india-full-report.doc [Accessed 27th September 2023].

Darbas, T., Brown, P.R., Das, K., Datt, R., Kumar, R., Pradhan, K. et al. (2020) *The feminization of agriculture on the Eastern Gangetic Plains: Implications for rural development*. Available from: https://scholar.google.com/citations?user=f1bfszsaaaaj&hl=en&oi=sra [Accessed 27th September 2023].

Derpsch, R. (2008) *Critical steps to no-till adoption. No-Till Farming Systems (Special Publication 3)*. Available from: http://www.rolf-derpsch.com/fileadmin/templates/main/downloads/steps.pdf [Accessed 27th September 2023].

Diagne, A. & Demont, M. (2007) Taking a new look at empirical models of adoption: average treatment effect estimation of adoption rates and their determinants. *Agricultural Economics*, 37(2–3), 201–210. Available from: https://doi.org/10.1111/j.1574-0862.2007.00266.x

Diiro, G. (2013) Impact of off-farm income on agricultural technology adoption intensity and productivity. *Agricultural Economics*, 11(2013), 1–15.

Dixon, J., Rola-Rubzen, M.F., Timsina, J., Cummins, J. & Tiwari, T.P. (2020) Socioeconomic impacts of conservation agriculture based sustainable intensification (CASI) with particular reference to South Asia. In: Dang, Y.P., Dalal, R.C. & Menzies, N.W. (Eds.) *No-till farming systems for sustainable agriculture*. Cham: Springer International Publishing, pp. 377–394.

Ekboir, J., Boa, K. & Dankyi, A.A. (2002) *Impact of no-till technologies in Ghana*. Mexico DF: CIMMYT.

Ericksen, P.J., Thornton, P.K., Notenbaert, A.M.O., Cramer, L., Jones, P.G. & Herrero, M.T. (2011) *Mapping hotspots of climate change and food insecurity in the global tropics: CGIAR research program on climate change, agriculture and food security*. Available from: https://cgspace.cgiar.org/handle/10568/3826 [Accessed 27th September 2023].

FAO. (2011) *The state of food and agriculture: women in agriculture*. Rome: Food and Agriculture Organization of the United Nations.

Farnworth, C.R., Baudron, F., Andersson, J.A., Misiko, M., Badstue, L. & Stirling, C.M. (2016) Gender and conservation agriculture in east and southern Africa: towards a research agenda. *International Journal of Agricultural Sustainability*, 14(2), 142–165. Available from: https://doi.org/10.1080/14735903.2015.1065602

Franzluebbers, A.J. (2002) Water infiltration and soil structure related to organic matter and its stratification with depth. *Soil and Tillage Research*, 66(2), 197–205. Available from: https://doi.org/10.1016/S0167-1987(02)00027-2

Fuglie, K.O. (1999) Conservation tillage and pesticide use in the Cornbelt. *Journal of Agricultural and Applied Economics*, 31(1), 133–147. Available from: https://doi.org/10.1017/S0081305200028831

García-Torres, L., Benites, J., Martínez-Vilela, A. & Holgado-Cabrera, A. (2010) *Conservation agriculture. Environment, farmers experiences, innovations, socio-economy, policy*. Dordrecht: Springer Netherlands.

Gathala, M.K., Ladha, J.K., Kumar, V., Saharawat, Y.S., Kumar, V., Sharma, P.K. et al. (2011) Tillage and crop establishment affects sustainability of south Asian Rice–wheat system. *Agronomy Journal*, 103(4), 961–971. Available from: https://doi.org/10.2134/agronj2010.0394

Gathala, M.K., Laing, A.M., Tiwari, T.P., Timsina, J., Islam, M.S., Chowdhury, A.K. et al. (2020) Enabling smallholder farmers to sustainably improve their food, energy and water nexus while achieving environmental and economic benefits. *Renewable and Sustainable Energy Reviews*, 120, 109645. Available from: https://doi.org/10.1016/j.rser.2019.109645

Gathala, M.K., Timsina, J., Islam, M.S., Rahman, M.M., Hossain, M.I., Harun-Ar-Rashid, M. et al. (2015) Conservation agriculture based tillage and crop establishment options can maintain farmers' yields and increase profits in South Asia's rice–maize systems: evidence from Bangladesh. *Field Crops Research*, 172, 85–98. Available from: https://doi.org/10.1016/j.fcr.2014.12.003

González-Flores, M., Bravo-Ureta, B.E., Solís, D. & Winters, P. (2014) The impact of high value markets on smallholder productivity in the Ecuadorean sierra: a stochastic production frontier approach correcting for selectivity bias. *Food Policy*, 44, 237–247. Available from: https://doi.org/10.1016/j.foodpol.2013.09.014

Gould, B.W., Saupe, W.E. & Klemme, R.M. (1989) Conservation tillage: the role of farm and operator characteristics and the perception of soil erosion. *Land Economics*, 65(2), 167. Available from: https://doi.org/10.2307/3146791

Govaerts, B., Sayre, K., Verhulst, N., Dendooven, L., Limon-Ortega, A. & Patiño-Zúñiga, L. (2008) *The effects of conversation agriculture on crop performance, soil quality and potential C emission reduction and C sequestration*. Available from: https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=4440adc32eff205258311efa24ae768eef170a33 [Accessed 27th September 2023].

Greene, W. (2010) A stochastic frontier model with correction for sample selection. *Journal of Productivity Analysis*, 34(1), 15–24. Available from: https://doi.org/10.1007/s11123-009-0159-1

Haider, M.Z., Ahmed, M.S. & Mallick, A. (2011) Technical efficiency of agricultural farms in Khulna, Bangladesh: stochastic frontier approach. *International Journal of Economics and Finance*, 3(3), 248–256. Available from: https://doi.org/10.5539/ijef.v3n3p248

Haque, M.E., Bell, R.W., Islam, M.A. & Rahman, M.A. (2016) Minimum tillage unpuddled transplanting: an alternative crop establishment strategy for rice in conservation agriculture cropping systems. *Field Crops Research*, 185, 31–39. Available from: https://doi.org/10.1016/j.fcr.2015.10.018

Hassane, A., Martin, P. & Reij, C. (2000) *Water harvesting, land rehabilitation and household food security in Niger: IFAD's soil and water conservation project in Illéla district*. Available from: https://www.africabib.org/rec.php?rid=337727422 [Accessed 27th September 2023].

Heckman, J.J. (1979) Sample selection bias as a specification error. *Econometrica*, 47(1), 153. Available from: https://doi.org/10.2307/1912352

Hobbs, P. (2007) Conservation agriculture: what is it and why is it important for future sustainable food production? *The Journal of Agricultural Science*, 145(2), 127. Available from: https://doi.org/10.1017/S0021859607006892

Hobbs, P., Gupta, R.A.J., Jat, R. & Malik, R.K. (2017) Conservation agriculture in the Indogangetic Plains of India: past, present, and future. *Experimental Agriculture*, 55(2), 339–357. Available from: https://doi.org/10.1017/S0014479717000424

Hossen, M.A., Hossain, M.M., Haque, M.E. & Bell, R.W. (2018) Transplanting into non-puddled soils with a small-scale mechanical transplanter reduced fuel, labour and irrigation water requirements for rice (*Oryza sativa* L.) establishment and increased yield. *Field Crops Research*, 225, 141–151. Available from: https://doi.org/10.1016/j.fcr.2018.06.009

Huang, C.J., Huang, T.-H. & Liu, N.-H. (2014) A new approach to estimating the metafrontier production function based on a stochastic frontier framework. *Journal of Productivity Analysis*, 42(3), 241–254. Available from: https://doi.org/10.1007/s11123-014-0402-2

Huang, G.B., Zhang, R.Z., Li, G.D., Li, L.L., Chan, K.Y., Heenan, D.P. et al. (2008) Productivity and sustainability of a spring wheat–field pea rotation in a semi-arid environment under conventional and conservation tillage systems. *Field Crops Research*, 107(1), 43–55. Available from: https://doi.org/10.1016/j.fcr.2007.12.011

Imbens, G.W. & Wooldridge, J.M. (2009) Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47(1), 5–86. Available from: https://doi.org/10.1257/jel.47.1.5

Islam, M.S., Anwar, M.M., Rashid, M., Hossain, A. & Kumar Ghosh, A. (2016) *Summary report of the post-Rabi and pre-Kharif focus group discussions in Rangpur District, Bangladesh*. Sustainable and Resilient Farming Systems Intensification (SRFSI) Project. RDRS Bangladesh.

Islam, S., Gathala, M.K., Tiwari, T.P., Timsina, J., Laing, A.M., Maharjan, S. et al. (2019) Conservation agriculture based sustainable intensification: increasing yields and water productivity for smallholders of the eastern Gangetic Plains. *Field Crops Research*, 238, 1–17. Available from: https://doi.org/10.1016/j.fcr.2019.04.005

Jat, H.S., Datta, A., Choudhary, M., Sharma, P.C. & Jat, M.L. (2021) Conservation agriculture: factors and drivers of adoption and scalable innovative practices in Indo-Gangetic plains of India – a review. *International Journal of Agricultural Sustainability*, 19(1), 40–55. Available from: https://doi.org/10.1080/14735903.2020.1817655

Karim, M.R., Moniruzzaman, M. & Alam, Q.M. (2010) Economics of hybrid maize production in some selected areas of Bangladesh. *Bangladesh Journal of Agricultural Research*, 35(1), 83–93.

Kasenge, V. (1998) Socio-economic factors influencing the level of soil management practices on fragile land. In: Shayo-Ngowi, A.J., Ley, G. & Rwehumbiza, F.B.R. (Eds.) *Proceedings of the 16th Conference of Soil Science Society of East Africa*. 13th–19th. December 1998, Tanga, Tanzania, Soil Science Society of Eastern Africa, pp. 102–112.

Kassam, A., Friedrich, T., Shaxson, F. & Pretty, J. (2009) The spread of conservation agriculture: justification, sustainability and uptake. *International Journal of Agricultural Sustainability*, 7(4), 292–320. Available from: https://doi.org/10.3763/ijas.2009.0477

Keil, A., Mitra, A., McDonald, A. & Malik, R.K. (2020) Zero-tillage wheat provides stable yield and economic benefits under diverse growing season climates in the eastern indo-Gangetic Plains. *International Journal of Agricultural Sustainability*, 18(6), 567–593. Available from: https://doi.org/10.1080/14735903.2020.1794490

Knowler, D. & Bradshaw, B. (2007) Farmers' adoption of conservation agriculture: a review and synthesis of recent research. *Food Policy*, 32(1), 25–48. Available from: https://doi.org/10.1016/j.foodpol.2006.01.003

Krishna, V.V. & Veettil, P.C. (2014) Productivity and efficiency impacts of conservation tillage in northwest indo-Gangetic Plains. *Agricultural Systems*, 127, 126–138. Available from: https://doi.org/10.1016/j.agsy.2014.02.004

Lai, C., Chan, C., Halbrendt, J., Shariq, L., Roul, P., Idol, T. et al. (2012) Comparative economic and gender, labor analysis of conservation agriculture practices in tribal villages in India. *International Food and Agribusiness Management Review*, 15(1), 73–86.

Lampurlanés, J. & Cantero-Martínez, C. (2006) Hydraulic conductivity, residue cover and soil surface roughness under different tillage systems in semiarid conditions. *Soil and Tillage Research*, 85(1–2), 13–26. Available from: https://doi.org/10.1016/j.still.2004.11.006

Li, L.L., Huang, G.B., Zhang, R.Z., Belloti, B., Guangdi, L. & Kwong, Y.C. (2011) Benefits of conservation agriculture on soil and water conservation and its progress in China. *Agricultural Sciences in China*, 10(6), 850–859. Available from: https://doi.org/10.1016/S1671-2927(11)60071-0

Mendola, M. (2007) Agricultural technology adoption and poverty reduction: a propensity-score matching analysis for rural Bangladesh. *Food Policy*, 32(3), 372–393. Available from: https://doi.org/10.1016/j.foodpol.2006.07.003

Mignouna, D., Manyong, V., Rusike, J., Mutabazi, K. & Senkondo, E.M. (2011) *Determinants of adopting Imazapyr-resistant maize technologies and its Impact of household Income in Western Kenya*. Available from: http://suaire.suanet.ac.tz/bitstream/handle/123456789/4155/determinantsadoptingimazapyr.pdf?sequence=2&isallowed=y [Accessed 27th September 2023].

Moreno, F., Murillo, J.M., Pelegrín, F. & Girón, I.F. (2006) Long-term impact of conservation tillage on stratification ratio of soil organic carbon and loss of total and active CaCO3. *Soil and Tillage Research*, 85(1–2), 86–93. Available from: https://doi.org/10.1016/j.still.2004.12.001

Ndlovu, P.V., Mazvimavi, K., An, H. & Murendo, C. (2014) Productivity and efficiency analysis of maize under conservation agriculture in Zimbabwe. *Agricultural Systems*, 124, 21–31. Available from: https://doi.org/10.1016/j.agsy.2013.10.004

Oduol, J.B.A., Binam, J.N., Olarinde, L., Diagne, A. & Adekunle, A. (2011) Impact of adoption of soil and water conservation technologies on technical efficiency: insight from smallholder farmers in sub-Saharan Africa. *Journal of Development and Agricultural Economics*, 3(14), 655–669. Available from: https://doi.org/10.5897/JDAE11.091

Orea, L. & Kumbhakar, S.C. (2004) Efficiency measurement using a latent class stochastic frontier model. *Empirical Economics*, 29(1), 169–183. Available from: https://doi.org/10.1007/s00181-003-0184-2

Potter, K.N., Torbert, H.A. & Morrison, J.E., Jr. (1995) Tillage and residue effects on infiltration and sediment losses on Vertisols. *Transactions of ASAE*, 38(5), 1413–1419. Available from: https://doi.org/10.13031/2013.27965

Prasad, R. (2005) Rice–wheat cropping systems. In: *Advances in agronomy*, Vol. 86. New York, NY: Elsevier, pp. 255–339.

Rahm, M.R. & Huffman, W.E. (1984) The adoption of reduced tillage: the role of human capital and other variables. *American Journal of Agricultural Economics*, 66(4), 405–413. Available from: https://doi.org/10.2307/1240918

Rahman, S. & Rahman, M.S. (2014) Exploring the potential and performance of maize production in Bangladesh. *International Journal of Agricultural Management*, 3(2), 99–106.

Rodriguez Sperat, R., Brugiafreddo, M.P. & Raña, E. (2017) Eficiencia técnica en la agricultura familiar: análisis envolvente de datos (DEA) versus aproximación de fronteras estocásticas (SFA). *Ns*, 9(18), 342–370. Available from: https://doi.org/10.21640/ns.v9i18.697

Rola-Rubzen, M.F., Sarmineto, J.M., Murray-Prior, R., Hawkins, J., Adhikari, S.P., Das, K.K. et al. (2019) *Impact of Conservation Agriculture for Sustainable Intensification (CASI) Technologies Among Men and Women Farmers in the Eastern Gangetic Plains of South Asia: Survey Results*. Australian Centre for International Agricultural and Research (ACIAR).

Rusinamhodzi, L., Corbeels, M., van Wijk, M.T., Rufino, M.C., Nyamangara, J. & Giller, K.E. (2011) A meta-analysis of long-term effects of conservation agriculture on maize grain yield under rain-fed conditions. *Agronomy for Sustainable Development*, 31(4), 657–673. Available from: https://doi.org/10.1007/s13593-011-0040-2

Sidhu, H.S., Jat, M.L., Singh, Y., Sidhu, R.K., Gupta, N., Singh, P. et al. (2019) Sub-surface drip fertigation with conservation agriculture in a rice-wheat system: a breakthrough for addressing water and nitrogen use efficiency. *Agricultural Water Management*, 216, 273–283. Available from: https://doi.org/10.1016/j.agwat.2019.02.019

Sinha, A.K., Ghosh, A., Dhar, T., Bhattacharya, P.M., Mitra, B., Rakesh, S. et al. (2019) Trends in key soil parameters under conservation agriculture-based sustainable intensification farming practices in the eastern ganga Alluvial Plains. *Soil Research*, 57(8), 883. Available from: https://doi.org/10.1071/SR19162

Solís, D., Bravo-Ureta, B.E. & Quiroga, R.E. (2007) Soil conservation and technical efficiency among hillside farmers in Central America: a switching regression model. *The Australian Journal of Agricultural and Resource Economics*, 51(4), 491–510. Available from: https://doi.org/10.1111/j.1467-8489.2007.00394.x

Somasundaram, J., Sinha, N.K., Dalal, R.C., Lal, R., Mohanty, M., Naorem, A.K. et al. (2020) No-till farming and conservation agriculture in South Asia – issues, challenges, prospects and benefits. *Critical Reviews in Plant Sciences*, 39(3), 236–279. Available from: https://doi.org/10.1080/07352689.2020.1782069

Somda, J., Nianogo, A.J., Nassa, S. & Sanou, S. (2002) Soil fertility management and socio-economic factors in crop-livestock systems in Burkina Faso: a case study of composting technology. *Ecological Economics*, 43(2–3), 175–183. Available from: https://doi.org/10.1016/S0921-8009(02)00208-2

Tamang, S., Paudel, K.P. & Shrestha, K.K. (2014) Feminization of agriculture and its implications for food security in rural Nepal. *Journal of Forest and Livelihood*, 12(1), 20–32.

Tessema, Y.M., Asafu-Adjaye, J. & Shiferaw, B. (2018) The impact of conservation tillage on maize yield and input demand: the case of smallholder farmers in North-West Ethiopia. *The Australian Journal of Agricultural and Resource Economics*, 62(4), 636–653. Available from: https://doi.org/10.1111/1467-8489.12270

Tsegaye, W., Aredo, D., La Rovere, R., Mwangi, W., Mwabu, G. & Tesfahun, G. (2008) *Does partial adoption of conservation agriculture affect crop yields and labour use? Evidence from two districts in Ethiopia*. CIMMYT/SG 2000 Monitoring and Impact Assessment (IA), Ethiopia Nippon IA Research Report No. 4.

Tsegaye, W., LaRovere, R., Mwabu, G. & Kassie, G.T. (2017) Adoption and farm-level impact of conservation agriculture in Central Ethiopia. *Environment, Development and Sustainability*, 19(6), 2517–2533. Available from: https://doi.org/10.1007/s10668-016-9869-5

Uaiene, R.N. (2011) Determinants of agricultural technology adoption in Mozambique. In *10th African Crop Science Conference Proceedings, Maputo, Mozambique, 10–13 October 2011*.

Villano, R., Bravo-Ureta, B., Solís, D. & Fleming, E. (2014) Modern Rice technologies and productivity in The Philippines: disentangling technology from managerial gaps. *Journal of Agricultural Economics*, 66(1), 129–154. Available from: https://doi.org/10.1111/1477-9552.12081

Wall, P.C. (2007) Tailoring conservation agriculture to the needs of small farmers in developing countries. *Journal of Crop Improvement*, 19(1–2), 137–155. Available from: https://doi.org/10.1300/J411v19n01_07

Winters, P., Salazar, L. & Maffioli, A. (2010) *Designing impact evaluations for agricultural projects. Impact evaluation guidelines. Technical notes no*. IDB-TN-198. Inter-American Development Bank. Available from: https://scholar.google.com/citations?user=qwbkyt4aaaaj&hl=en&oi=sra [Accessed 27th September 2023].

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Paz, B., Hailu, A., Rola-Rubzen, M.F. & Rashid, M.M. (2024) Conservation agriculture-based sustainable intensification improves technical efficiency in Northern Bangladesh: The case of Rangpur. *Australian Journal of Agricultural and Resource Economics*, 68, 125–145. Available from: https://doi.org/10.1111/1467-8489.12537