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RESEARCH ARTICLE

A metafrontier approach and fractional regression model to analyze the environmental efficiency of alternative tillage practices for wheat in Bangladesh

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Abstract

Among alternative tillage practices, conservation tillage (CT) is a prominent greenhouse gas (GHG) mitigation strategy advocated in wheat cultivation, largely because of its low energy consumption and minimum soil disturbance during cultural operations. This paper examines the agricultural production and GHG emission trade-off of CT *vis-à-vis* traditional tillage (TT) on wheat farms of Bangladesh. Using a directional distance function approach, the maximum reduction in GHG emissions was searched for within all available tillage technology options, while increasing wheat production as much as possible. The underlying institutional, technical, and other socio-economic factors determining the efficient use of CT were analyzed using a fractional regression model. The average meta-efficiency score for permanent bed planting (PBP) and strip tillage (ST) was 0.89, while that achieved using power tiller operated seeders (PTOS) is 0.87. This indicates that with the given input sets, there is potential to reduce GHG emissions by about 11% for ST and PTOS; that potential is 13% for farmers using PTOS. The largest share of TT farmers cultivate wheat at lower meta-efficiency levels (0.65–0.70) compared to that observed with farmers practicing CT (0.75–0.80). Fractional regression model estimates indicate that an optimal, timely dose of fertilizers with a balanced dose of nutrients is required to reduce GHG emissions. To develop climate smart sustainable intensification strategies in wheat cultivation, it is important to educate farmers on efficient input management and CT together. Agricultural development programs should focus on addressing heterogeneities in nutrient management in addition to tillage options within CT.

Keywords Climate smart agriculture, Sustainable intensification, Conservation tillage · Directional distance function · Fractional regression model · Greenhouse gas emission

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Introduction

Agriculture is a major source of global environmental problems including climate change, biodiversity loss, soil degradation, and loss of water quality and quantity (McNunn et al., 2020). In the case of climate change, agricultural land uses are widely acknowledged to contribute ca. 19–20% of greenhouse gas (GHG) emissions globally from anthropogenic activities (Jantke et al., 2020). When considering the entire production and supply chain of agriculture and food production, these emissions would reach up to 29% of global GHG emissions (Vermeulen et al., 2012). GHG emissions from agriculture are influenced enormously by farmer decisions on the intensity and frequency of material inputs and cultivation practices such as tillage (Martin-Gorriz et al., 2020).

Though concern over the negative environmental externalities of mounting atmospheric GHG concentrations has escalated in the past decade, sustainable and environmentally desirable agricultural development remains an elusive goal, particularly in developing countries (Antle and Diagana, 2003). In countries that have large-scale food security problems, the policy environment often favors the use of input-intensive technologies, and can be biased against climate-smart-sustainable intensification (SI) alternatives. Although SI implies methods that increase agricultural yields without adverse environmental impact and without the conversion of additional non-agricultural land to cultivation (Pretty and Bharucha, 2014), in practice, SI alternatives may suffer from trade-offs between economic performance and environmental sustainability (Kanter et al., 2018), with important implications for shaping agricultural policies in developing countries. Achieving both environmental and economic efficiency is important because improving the former can be a cost-efficient way of reducing undesirable environmental impact, and SI policies that aim to improve environmental efficiency may also be easier to implement than drastic measures that aim to restrict the level of economic activity to meet conservation goals (Picazo-Tadeo et al., 2011). This paper explores the trade-off and synergies between the production and environmental impact of conservation tillage (CT), and its scope as a potential alternative to traditional tillage (TT) or conventional practices for environment-friendly, yet productive, agriculture, using wheat farming systems in Bangladesh as a case study. We compared the environmental efficiency (EE) of TT against the three main CT practices adopted by wheat farmers in Bangladesh, namely (1) permanent bed planting (PBP), (2) crop establishment with a power tiller operated seeder (PTOS), and (3) strip tillage (ST).

Conservation tillage is an umbrella term for a range of residue management and no till or reduced tillage practices (Horwath and Kuzyakov, 2018). In addition, numerous experiments have confirmed the advantages of the split application of fertilizers to synchronize the supply of nutrients with crop demand and limit losses to the environment. An optimal, timely dose of balanced nutrients can aid crop production, enhance economic performance, and minimize environmental externalities. At the same time, the fertilizer response to irrigation can affect production–emission trade-offs. In addition, CT practices have been reported to reduce GHG emissions from primary sources of emissions (land tillage and sowing) and also indirectly through decreased use of fossil fuels in field preparation. Such reductions are achieved by replacing inversion plowing, while combining seeding and tillage into a single operation that saves fossil fuel use. As CT limits soil disturbance, the long-term adoption of CT can restore soil structure and enhance activity of soil biota that are critical to sequestering carbon in the soil (Lal 2015). In this study, however, we adopt a broad definition of CT to a reduction in frequency of tillage passes and in conjunction with the usage of direct seeding equipment (Gathala et al., 2016).

The available literature on the environmental dimensions of CT has three key shortcomings. First, there is a dearth of evidence on the actual efficiencies of the cropping system process under on-farm conditions as practiced by farmers themselves, rather than on research stations. Despite this, CT is frequently promoted as one among the best potential mitigation strategies – at times with debatable consequences (Powlson et al., 2014) – because it aims at reducing environmental impact by combining reduced tillage operations (to minimize soil disturbance) with the efficient use of input resources (Feng et al., 2018). Reducing tillage operation frequency, for instance, the use of no-tillage including zero-tillage coupled with controlled traffic systems have potential to reduce GHG emissions and enhance C sequestration in arable land, even in situations where high nitrogen rates are used (Gasso et al., 2014; Antille et al., 2015). As such, empirical evidence on the environmental impact of CT is limited mostly to the agronomic dimensions, such as soil carbon sequestration (Powlson et al., 2014), nutrient loss and water quality (Munodawafa and Zhou, 2008), and assessments of the consequence of these practices on biodiversity (Palm et al., 2014). Second, CT is widely promoted as a climate smart farming practice, and the IPCC Fourth Assessment Report underscores its potential to mitigate GHG emissions (Thierfelder et al., 2017) although the potential for conservation agriculture to improve soil carbon storage at increasing soil depth has been questioned (Powlson et al., 2014). Finally, though studies explore the environmental impact of CT versus conventional/traditional tillage (TT) (Haddaway et al., 2017), there are still relatively few examples that comprehensively explore the trade-offs or synergies between production, profitability, and environmental goals across different CT approaches. Consequently, this article addresses the above-discussed research gap by estimating the environmental efficiency (EE) of wheat farmers using different types of CT practices, by testing the following two hypotheses:

1. Environmentally, CT is a more appropriate crop production approach than conventional tillage.
2. Agricultural production–emission trade-offs will vary with technology options, and are influenced by socio-economic and institutional factors affecting farmers.

To test the first hypothesis, we carried out an environmentally sensitive efficiency analysis. Using the directional distance function (DDF) approach, the maximum contraction of environmentally detrimental output is searched for within the technology options available at the observed level of inputs, while expanding the desired output as much as possible. The second hypothesis, which is concerned specifically with the environmental impact of CT technology on households, is tested through a meta-frontier approach, along with a fractional regression model (FRM).

As a case study, this paper based on observed wheat cultivation data from adopters of CT (i.e., those farmers who have adopted PBP, PTOS, and ST) and practitioners of TT in the eastern Indo-Gangetic plains of Bangladesh.

The remainder of the paper is structured as follows. The first part of the methodology ("Methodology") discusses the theoretical and econometric foundation of environmental efficiency and factors determining it. The second part details the study area, sampling, and data collection. "Results and discussion" discusses the results, while the "Conclusion" concludes the paper by providing key insights and messages distilled from the study.

Methodology

Agricultural production model with undesirable output

Agriculture involves the joint production of desirable (marketed or good) output and undesirable (non-marketed or bad) outputs; for example, crop cultivation typically makes use of external inputs, such as fertilizers or insecticides, that can result in undesirable environmental externalities, including GHG emissions. Thus, in this production setting, the production process involves—apart from the desirable output of wheat grain—the undesirable externality of GHG emissions and consequental climate change. Thus, the joint production of desirable and undesirable outputs can be expressed in terms of feasible output sets $P(x), x \in \mathfrak{R}_+^M$ (Ball et al., 2001):

$$P(x) = \left[\left(y_g, y_b\right) | \left(x, y_g, y_b\right) \in T \right] \tag{1}$$

$$\text{where,} T = \left[\left(x, y_g, y_b\right) | x \text{ can produce } \left(y_g, y_b\right) \right] \tag{2}$$

In Eqs. (1) and (2), $y_g \in \mathfrak{R}_+^1$ denote wheat grain (the desirable output), $y_b \in \mathfrak{R}_+^1$ indicates GHG emissions (undesirable output), and $x \in \mathfrak{R}_+^M$ represents external inputs. Earlier assessments treated environmental externalities (to air, water, and ground) and side effects (such as pesticide poisoning) as inputs in the production activity. Estimating the efficiency of technology adoption involves the application of either one of two general approaches including parametric stochastic frontier analysis (SFA) and/or nonparametric data envelopment analysis (DEA) (Manjunatha et al., 2016). Recent studies (e.g., Dong et al., 2018; Le et al., 2019) employed linear programming–based *traditional* data envelopment analysis (DEA) to model GHG emissions from agricultural production, by treating undesirable outputs (GHG emission) as inputs in the DEA. The approach of considering undesirable outputs as inputs is inconsistent with the principles of production ecology as they modeled the technology studied with an unbounded output set, thus failing to satisfy the standard axioms of production theory (Färe and Grosskopf, 2004). We overcome this limitation of *traditional* DEA through a novel directional distance function (DDF) approach, which models undesirable emissions as outputs, by satisfying the following six axioms of agricultural production:

1. Inactivity: It is possible to produce neither desirable nor undesirable output for any given input vector.
2. Compactness: Finite inputs can only produce finite outputs.
3. Inputs are freely disposable. However, in the setting of agricultural production, this axiom implies that it is possible to incorporate multiple inputs as well as a single input in examining the correlation of input variables (Macpherson et al., 2010).
4. Null-jointness: In the given technology of production, it is impossible to produce wheat grain without producing GHGs.
5. Strongly disposable desirable (good) output: The farmer may freely dispose of good output.
6. Weakly disposable undesirable (bad) outputs: Reducing grain yield could potentially reduce GHGs; that is, the private cost of reducing environmental emission is non-zero and positive.

Directional distance function approach

The desired direction of the environmental–economic DDF for crop production is the maximum expansion of wheat production in the d^g direction with the largest feasible proportional contraction in inputs and GHGs in the $-d^x$ and $-d^b$ directions, respectively. While considering resource use optimization and the environmental externality reduction that could be accrued with CT, we define environmentally sensitive agricultural production in terms of the DDF approach, wherein the maximum contraction of environmentally detrimental output is searched for within the technology options available at the observed level of inputs while expanding wheat production as much as possible (Fig. 1).

Mathematically, the directional distance function can be defined as

$$\vec{D}_T(x, y_g, y_b; d) = \sup\left[\delta : \left(y_g + \delta^g d^g, y_b - \delta^b d^b\right) \in P(x - \delta^x d^x)\right] \tag{3}$$

where $d = (-d^x, d^g, -d^b)$. Under the properties of null-jointness, jointly weak disposability of desirable and undesirable outputs, and strong disposability of desirable output, the value δ^g measures the productive technical inefficiency; δ^b is the environmental efficiency (EE); and δ^x is the input use efficiency, and Eq. (3) seeks the maximum attainable expansion of desirable outputs in the d^g direction and the largest feasible contraction of undesirable outputs and inputs in d^b and d^x directions (Färe and Grosskopf, 2004).

We illustrate the directional distance function using Fig. 1, by assuming that the production process consists of one desirable and one undesirable output and that the input vector is held at constant level. As stated in Eq. (3), the objective of the environmental DDF is to expand the production in the desired direction (d^g), while contracting the undesirable output to the minimum level possible (d^b direction). Let the production feasibility set under weak disposability assumption in Fig. 1 is denoted by the points "*RTUVW*." This production feasibility set represents the global/meta-production frontier (P^G), which encompasses all group frontiers (an example of group frontier in Fig. 1 is P^{TT}). That is, all the group benchmark tillage technologies (strip tillage (P^{ST}), permanent bed planting (P^{PBP}), power tiller operated seeder (P^{PTOS}), and traditional tillage (P^{TT})) are enveloped by a global benchmark technology (P^G) forming a single production feasible set from the all tillage technologies. For the detailed information of tillage technologies studied here, please refer to supplementary material SM Table 1.

$$P^G = P^{ST} \bigcup P^{PBP} \bigcup P^{PTOS} \bigcup P^{TT} \tag{4}$$

Consider farm A, which is under-producing y_g and over-producing y_b. The objective of the DDF model is to move A to $f_w\,(y_b - \delta^b/d^b, y_g + \delta^g/d^g)$ by assuming weak disposability of GHG emission. To operationalize the DDF models, we adopt the activity analysis in the following formulation for decision making unit (farm) $i = 1, \ldots, N$ producing one desirable (good) output and one undesirable (bad) output using $k = 1, \ldots, K$ inputs with the assumption of jointly weakly disposable outputs (Färe and Grosskopf, 2004; Macpherson et al., 2010):

$$\vec{\mathbf{D}}\left(x_{i^*}, y_g^{i^*}, y_b^{i^*}; d\right) = \max \delta_{i^*} \tag{5}$$

$$\text{subjectto}: \begin{array}{c} \sum_{i=1}^{N} z_i y_g^i \ge y_g^{i^*} + \delta_g^{i^*} d^g \\ \sum_{i=1}^{N} z_i y_b^i = y_b^{i^*} - \delta_b^{i^*} d^b \\ \sum_{i=1}^{N} z_i x_{ik} \le x_{i^*k} k - \delta_x^{i^*k} d^x = 1, \ldots .K \\ z_i \ge 0 i = 1, \ldots .., N \end{array}$$

where z is the intensity variable. The second constraint explains that the undersireable output is weakly disposable. The expansion factor δ measures the distance from the observed performance of the farm to the production frontier at the boundary of the feasible production set in the desired direction:

$$d = \{\mathrm{Max}(y_g), \mathrm{Min}(y_b), \mathrm{Min}(d^x)\} \tag{6}$$

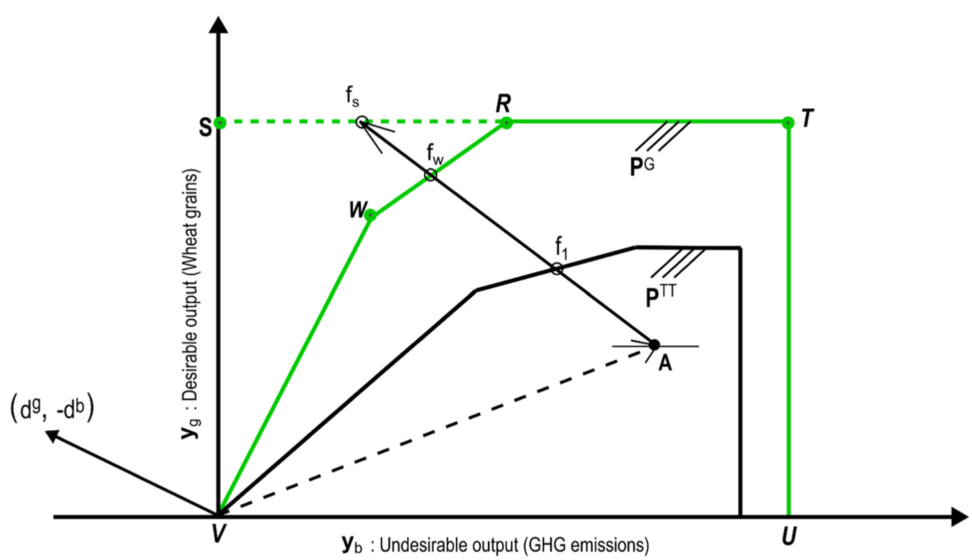

Fig. 1 Directional distance function and global Malmquist-Lueneberge productivity index

Alternatively, if δ_i is equal to zero, the farm i lies on the production possibility frontier. Farms lying on the frontier have efficiency scores of 1.0, and they are 100% efficient (Saravia-Matus et al., 2021). Here, δ does not require any functional form specification, but is sensitive to measurement units and the magnitude of the variable. This sensitivity causes serious problems, as inconsistency is very common across agri-environmental variables (Macpherson et al., 2010). To manage this sensitivity, we transformed the variables to:

$$y_g^* = \frac{y_g}{y_g^{\max}}; \tag{7}$$

$$y_b^* = \frac{y_b}{y_b^{\max}}; \tag{8}$$

$$x_k^* = \frac{x_k}{x_k^{\max}} \forall k \tag{9}$$

Under this transformation, δ is similar to an elasticity measure (Picazo-Tadeo et al., 2011), and is equivalent to the maximum increase (decrease) in desirable outputs (inputs and undesirable outputs) as a percentage of the maximum observation for each variable in the dataset (Macpherson et al., 2010). In our efficiency analysis, we convert the Shephard distance function to the Farrell efficiency score, in which an efficiency score of unity indicates a technically efficient farm, and an efficiency score of less than unity indicates a technically inefficient farm.

Technology gap—meta technology ratio

Let $\vec{D}_k(x, y_g, y_b; d)$ be the output-oriented distance function for the group frontier representing the group benchmark technology $(\mathrm{P}^{\mathrm{k}})$, which is defined as

$$\mathrm{P}^{\mathrm{k}} = \left\{\mathrm{P}^{\mathrm{ST}}, \mathrm{P}^{\mathrm{PBP}}; \mathrm{P}^{\mathrm{PTOS}}, \mathrm{P}^{\mathrm{TT}}\right\} \tag{10}$$

and $\vec{D}_G(x, y_g, y_b; d)$ be that of meta-frontier representing global technology (P^{G}). The technology gap ratio (*MTR*) can be then defined as

$$\mathrm{MTR}^k(x, y_g, y_b; d) = \vec{D}_G(x, y_g, y_b; d) - \vec{D}_k(x, y_g, y_b; d) \tag{11}$$

This can be illustrated using Fig. 1 for farm A, cultivating wheat using TT, where

$$\mathrm{MTR}^{\mathrm{TT}}(x, y_g, y_b; d) = \vec{D}_G(x, y_g, y_b; d) - \vec{D}_{\mathrm{TT}}(x, y_g, y_b; d) \tag{12}$$

Let the distance Af_1 in Fig. 1 represent the relative position of the farm with reference to the group frontier, and Af_{w} is the distance from global frontier. Thus,

$$\vec{D}_G(x, y_g, y_b; d) - \vec{D}_{TT}(x, y_g, y_b; d) = Af_w - Af_1 \tag{13}$$

$$\mathrm{MTR}^{\mathrm{TT}}(x, y_g, y_b; d) = Af_w - Af_1 \tag{14}$$

Determinants of environmental-economic efficiency: fractional regression model estimation

Despite the problems of linearity and truncation assumptions, the conventional Tobit models so far employed in the second stage regression of efficiency scores to analyze the factors determining (in)efficiency assume that the same environmental variables affect both efficient and inefficient farms alike. However, when the probability of observing efficient farms is relatively large — as in our case, when the sample size is low — one may suspect that the sources of farm efficiency may differ from those of farm inefficiency (Ramalho et al., 2010). Hence, a two-part model that avoids problems associated with using linear and Tobit models in the DDF framework could be the best way to explain both efficiency and inefficiency effects in our study.

We employ the FRM adapted to the DEA framework by Ramalho et al. (2010). The first part of the FRM comprises a standard binary choice model that governs the probability of observing an efficient wheat farm.

The conditional probability of observing an efficient wheat farm is specified as

$$\Pr(m = 1|x) = E(m|x) \tag{15}$$

$$E(m|x) = F(x\beta_{1p}), m = \begin{cases} 1 for \delta = 0 \\ 0 for 0 < \delta < 1. \end{cases} \tag{16}$$

where m is a binary variable that can take 1 and 0 values for efficient and inefficient wheat farms respectively. In our study, model specification of $F(x\beta_{1p})$ is identified using tests proposed by Ramalho et al. (2010). Equation (16) could be estimated by the maximum likelihood method using the whole sample of farms. The second component of FRM is a fractional part estimated using part of the sample consisting inefficient farms ($\omega = (1 - \delta^b) < 1$), and governs the magnitude of the DDF efficiency scores on the interval [0, 1], as

$$E(\omega|x, \omega \in]0, 1[) = M(x\beta_{2p}) \tag{17}$$

where ω denotes the efficiency score with $\delta > 0$. $M(.)$. Depending on the tests performed for $E(\omega|x)$ in the FRM's first part (where β_{2p} is the vector of exogenous factor coefficients), the model was specified for both the binary and fractional part of analysis. The RESET (Regression Equation

Specification Error Test), the GGOFF (Generalized goodness-of-functional form) test, and p-tests were used to test the correct specification of the conditional expectation $E(\omega|x)$ of the dependent variable in the FRM. For estimation purpose, these models have been implemented in R (R 3.2.1).

Data and study area

The present study is based on primary data collected from wheat farming households ($N=140$) and custom service (tillage) providers ($N=35$) in three wheat producing districts in the eastern Indo-Gangetic Plains of Bangladesh (namely, Dinajpur, Rajshahi, and Nilphamari) (Fig. 1) during the summer 2012 (April–June), following the previous season in which wheat was produced in the winter. The farm household data were collected through personal interviews, using structured questionnaires, whereas focus group discussions were also conducted for collecting data pertaining to tillage machinery operations. The selection of households followed a random sampling procedure among villages where CT is practiced by farmers alongside traditional tillage (Table 1) (Fig. 2).

In this study, under the broad umbrella of CT, we consider three major tillage options available for wheat: permanent bed planting (PBP), power tiller-operated seeder (PTOS), and strip tillage (ST). This disaggregation of CT technology captures the potentially differential impacts of tillage on yield and efficiency, which was largely unrecognized in previous studies that used more confined technology definitions (Cf. Erenstein (2009). Therefore, wheat-growing households are first grouped into CT adopters and non-adopters for the 2011–2012 crop season and, within the adopters' group, farmers are sorted by the type of CT. The final sample for this study comprises 105 CT adopters (35 each belonging to PBP, ST, and PTOS) and 35 non-adopters.

The summary statistics in Table 1 provide insight into the input and outputs used in the DDF model as well as into the explanatory variables used in the second stage FRM. The variables used in the estimations can be grouped into input, output, farm household, and management variables. On average, CT adopters are better educated than non-adopters and are better exposed to training programs on conservation agriculture. The GHG emissions (i.e. carbon dioxide (CO_2), nitrous oxide (N_2O), methane (CH_4)) from crop production can originate from primary, secondary, and tertiary sources. According to Lal (2004), primary sources of GHG emissions are due to either mobile operations (e.g., tillage, sowing, harvesting, and transport), or stationary operations (e.g., water pumping, energy for post-harvest processing, etc.). Secondary sources comprise manufacturing, packaging, and storing fertilizers and pesticides. Tertiary sources include acquisition of raw materials and fabrication of equipment and farm buildings. In the case of wheat in Bangladesh, the main sources of energy-based GHG emissions are either primary (e.g., tillage and pumping for irrigation) or secondary (e.g. fertilizers). It is beyond the scope of this study to consider activities leading to tertiary emissions from building farm and field infrastructure, field irrigation channels, etc. In addition, accounting for emissions that originate from soil biological processes was also not possible under this study. Therefore, we capture two types of emission sources (primary and secondary) as undesirable outputs in the DDF model, specifically by imputing the quantity of fossil fuels (for on-farm operations including tillage and irrigation), fertilizers, and agro-chemicals consumed at the plot level. For detailed explanation on our emission calculations, see Appendix A1.

Since CT adopters are segregated from non-adopters (TT) based on the type of tillage operations involved in the main wheat plot, these input variables are measured at the level of the main wheat plot, to increase data accuracy. The inputs in the DDF are the plot level measures of variables: area of the main wheat plot, quantity of nitrogen, phosphorus, potash (NPK) fertilizers, fuel and seed, volume of irrigation water, and amount of labor. The groups differ in terms of chemical fertilizer, fuel, and labor. The use of NPK fertilizers by CT adopters (averaging 106:57:80 kg ha^{-1}) and that of non-adopters (Averaging 119:64:93 kg ha^{-1}) differs from the recommended rate of NPK fertilizer in this region (100:90:45 kg ha^{-1}), largely with respect to phosphorus and potash fertilizers.

However, in the studied farms, the use of plant protection chemicals (0.61 kg ha^{-1}) is about half the dose (1.25 kg ha^{-1}) recommended by the Bangladesh Agricultural Research Institute. The use of inputs such as fuel, labor, irrigation, seed, phosphorous, and potash fertilizers was found to be significantly higher among non-adopters than CT adopters. Though the farmers studied differ in their consumption of potash and phosphorus, they are similar in their use of nitrogen as well as the pesticide that contribute as secondary sources environmental externalities. In order to achieve nutrient use efficiency and to mitigate GHG emissions from fertilizer application, the 4R principles of nutrient management can be beneficial (Bindraban et al., 2015). The 4R's of fertilizer nutrient management stand for right source, right rate, right time, and right place.

Already, several agronomic on-station experiments have confirmed the advantages of the split application of fertilizers: improvement in plant uptake and reduction in the negative environmental externalities as pollution. An optimal, timely dose of fertilizers is required, along with a balanced dose of nutrients, such that crop production is economically profitable, and its environmental externalities minimal. At the same time, the fertilizer response to

Table 1 Summary statistics

Variables	All samples ($N=140$) Mean (SE)	CT ($N=105$) Mean (SE)	TT ($N=35$) Mean (SE)
Farm household variables			
Cultivable land owned (ha)	0.63 (0.05)	0.67 (0.06)	0.50 (0.09)
Educational level of the farmer (years)	6.95 (0.31)	7.50** (0.37)	5.29 (0.45)
Age of the farmer (years)	46.20 (1.08)	45.75 (1.19)	47.54 (2.46)
Training on conservation agriculture (number of training events attended)	1.66 (0.14)	2.01** (0.16)	0.60 (0.13)
Experience in conservation tillage (years)	2.51 (0.21)	3.35*** (0.28)	0.00 (0.00)
Involvement in farming (1 = full, 2 = partial, and 3 = no involvement)	1.45 (0.05)	1.43 (0.06)	1.51 (0.10)
Access to credit (Yes = 1, otherwise = 0)	0.34 (0.04)	0.29 (0.04)	0.49* (0.09)
Remoteness (km)	0.26 (0.03)	0.24 (0.04)	0.30 (0.05)
Distance to the nearest extension service office (km)	13.72 (1.47)	9.25*** (1.49)	27.11 (2.86)
Farm household size (numbers)	5.01 (0.20)	4.93 (0.24)	5.26 (0.42)
Off-farm income (%)	25.29 (2.15)	26.43 (2.50)	21.86 (4.22)
Output variables[a]			
Wheat yield (t ha^{-1})	3.93 (0.05)	4.01** (0.07)	3.68 (0.05)
Greenhouse gas emission (kg CO_2eq ha^{-1})[b]	415.49 (8.82)	393.80* (10.35)	480.56 (11.12)
Input variables[a]			
Seed (kg ha^{-1})	141.12 (3.03)	128.36** (2.65)	179.39 (5.35)
Nitrogen fertilizers applied (kg ha^{-1})	109.39 (2.80)	106.31 (3.48)	118.62 (3.79)
Phosphorus fertilizer applied (kg ha^{-1})	58.81 (1.57)	56.94* (1.83)	64.41 (1.57)
Potash fertilizer applied (kg ha^{-1})	83.28 (2.44)	80.11** (2.99)	92.78 (3.45)
Fuel use (L ha^{-1})[c]	43.52 (1.38)	38.00** (1.28)	60.06 (2.30)
Pesticide use (kg ha^{-1})	0.61 (0.10)	0.67 (0.13)	0.42 (0.08)
Labor (h ha^{-1})	674.31 (36.90)	584.93*** (34.86)	942.44 (91.08)
Irrigation (m^3 ha^{-1})	1479.52 (70.29)	1386.22* (73.91)	1759.41 (166.12)
Wheat main plot (ha)	0.15 (0.01)	0.15 (0.02)	0.17 (0.02)
Management related variables			
Advice received from input dealer (numbers)	0.99 (0.08)	1.13** (0.09)	0.57 (0.12)
Application of NPK fertilizers in splits (Yes = 1, otherwise = 0)	0.42 (0.04)	0.42 (0.05)	0.43 (0.08)
Application of N- fertilizer before irrigation (Yes = 1, otherwise = 0)	0.42 (0.04)	0.45 (0.05)	0.34 (0.08)
Delay in N-fertilizer application at tillering stage (Yes = 1, otherwise = 0)	0.39 (0.04)	0.66** (0.08)	0.30 (0.04)
Awareness on soil and water conservation (Yes = 1, otherwise = 0)	0.44 (0.04)	0.55*** (0.05)	0.11 (0.05)

[a]Measured at the farmers' primary wheat field level, standard errors in parenthesis; *, **, and *** mean differences between CT and TT farms are significant at the 10%, 5%, and 1% levels, respectively

[b]The kilogram CO_2 equivalents (kg CO_2eq) computed using standard conversion factors/coefficients given in Appendix Table A1

[c]Fuel use measured from both tillage and irrigation operations

irrigation can affect the production–emission trade-off. To capture this, we included—along with other conventional exogenous factors—three fertilizer-related tillage-specific management variables: dummies for (1) application of NPK fertilizers in splits, (2) application of N-fertilizer before irrigation, and (3) the delay in N fertilizer application following the maximum tillering stage of wheat. Table 1 also shows that compared to adopters (30%), non-adopters (66%) tended to delay their N fertilizer application after the maximum tillering stage. Best management practices for wheat recommend timely and split application of fertilizers during critical periods of growth, only 42% of CT adopters applied fertilizers in splits; this indicates that many are still learning how to adopt the CT technology effectively.

Results and discussion

Environmentally sensitive production efficiency of conservation tillage

Table 2 presents the EE estimates under both constant (CRS) and variable return to scale conditions (VRS) by employing

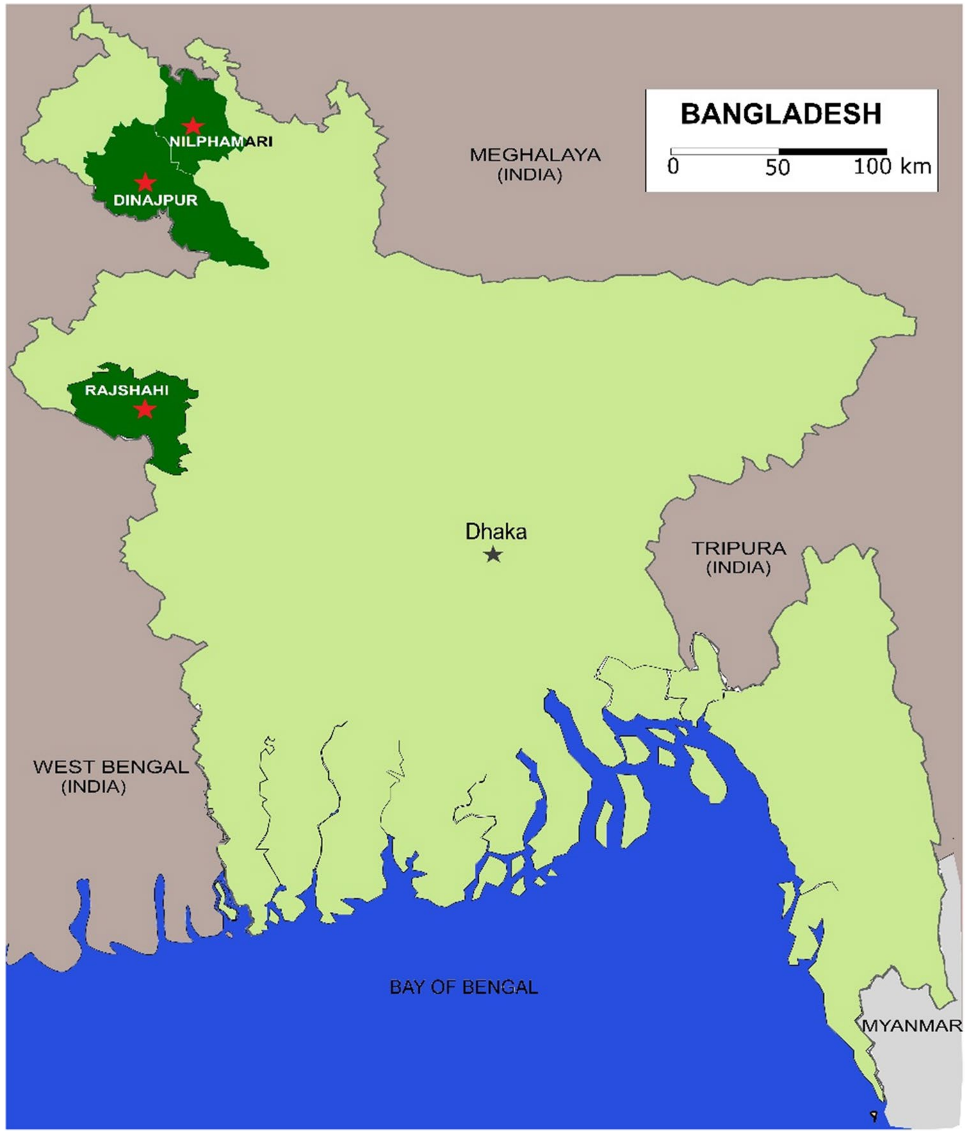

Fig. 2 Map of Bangladesh showing study districts

the DDF model. With different tillage options used in the different study regions, the environmental efficiency measures based on the VRS assumption would sub-divide the data into sets of farmers achieving similar returns to scale. This may potentially lead to the domination of those farms considered efficient within their peer groups for specific tillage technology types across all attributes within other scaled peer groups as well (Ferraro, 2004). Hence, the estimates and efficiency effects in this paper are focused largely under the CRS framework.

Table 2 Directional distance function (DDF) and technology gap ratio (MTR) of wheat farmers with respect to tillage-specific frontiers and meta-frontier estimates

Efficiency	DDF-CRS				DDF-VRS			
	PBP	PTOS	ST	TT	PBP	PTOS	ST	TT
Tillage-specific EE	0.90 (0.12)	0.92 (0.09)	0.95 (0.08)	0.99 (0.02)	0.95 (0.09)	0.96 (0.07)	0.99 (0.04)	0.99 (0.01)
Meta-frontier EE	0.89*** (0.12)	0.87*** (0.11)	0.89*** (0.12)	0.72 (0.06)	0.92*** (0.10)	0.90*** (0.11)	0.93*** (0.11)	0.74 (0.07)
MTR	0.99 (0.03)	0.94 (0.06)	0.94 (0.08)	0.72 (0.05)	0.97 (0.06)	0.93 (0.08)	0.94 (0.10)	0.74 (0.06)

"***" = null of equality of distributional densities to EE (Li et al., 2009) of TT is rejected at the 0.1% level. CT and TT stand for conservation and traditional tillage. PBP, PTOS, ST indicate permanent bed planting, power tiller operated seeding, and strip tillage

Tillage-specific efficiency

To get first-hand information on the environmentally sensitive production efficiency of farms within a tillage technology set, the tillage-specific efficiency scores of farmers are estimated using their tillage groupings during benchmarking. Table 2 reports the average EE scores relative to the individual tillage-specific DDF frontier and meta-frontier technologies, alongside MTR scores of CT adopters (including for PBP, PTOS, and ST) and non-adopters (TT). The average tillage-specific efficiency scores in the DDF are estimated at 0.90, 0.92, 0.99, and 0.99 for farms practicing PBP, PTOS, ST, and TT, respectively. The efficiency ranges for PBP, PTOS, ST, and TT are 0.65–1.00, 0.76–1.00, 0.74–1.00, and 0.92–1.00, respectively. The ranges of tillage-specific DDF efficiency scores display a wider spread for CT adopters than for non-adopters. While the efficiency ranges of ST and PTOS are broader than that of non-adopters, an even wider range of efficiency (0.65–1.00) is observed for PBP farms. This indicates considerable operational heterogeneity within the tillage option, and could be due to the differential adoption behavior of farmers (according to Aravindakshan et al. (2015), a small portion of farmers tend to reinvent CT by combining TT practices). On the other hand, the efficiency estimates of TT have a smaller range (0.92–1.00), which suggests that conventional farms are more or less homogenous in production practices. However, further interpretation based on the tillage-specific efficiency score is quite misleading, as it envelops only one tillage technology at a time, without considering other technologies available to farmers.

Meta-frontier efficiency and technology gap

Table 2 presents the results of the meta-frontier environmental efficiency (meta- frontier EE) estimates. It shows that 30% of sample farms cultivate on the DDF meta-frontier. The average meta-frontier EE scores are estimated at 0.89, 0.89, 0.87, and 0.72 for farms practicing PBP, ST, PTOS, and TT, respectively. The corresponding meta-frontier EEs will be 89%, 89%, 87%, and 72% for PBP, ST, PTOS, and TT farmers, respectively. This indicates that with the given input sets observed in our surveys, there is a potential to reduce GHG emission by about 11% in the case of both PBP and ST; that potential is conversely 13% for PTOS farmers. The largest share of TT farmers cultivate wheat at considerably lower meta-efficiency levels (0.65–0.70) compared to that of CT farmerss (0.75–0.80). Many of the CT farmers showed high efficiency (0.85–1.0), and all meta-frontier farms were CT adopters. The mean EE achieved by CT farmers is 88%, which is substantially higher than those following traditional tillage techniques (72%). This difference is clearly shown by bean density plots displayed in Fig. 3 A and B. One of the possible reasons for this behavior is path dependency emerging from farmers' familiarity from 'green revolution' type technology approaches, in which more fertilizer-responsive semi-dwarf varieties produce more grain yield per unit of additional fertilizer. However, over the years, a yield plateau has reached in many countries, with only incremental gains being made (Lin and Huybers, 2012). Conversely, the continued increased use of fertilizers without appropriate cultivars that can capture nutrients and convert them to economic yield is associated with reduced nitrogen use efficiency and GHG emissions. Options to improve efficiencies, however, do appear to exist within the group of farmers studied. Our estimates showed a positive signal, as the traditional farms could drastically reduce GHG-emitting inputs (N, P, pesticides, and fossil fuels) without compromising existing yield levels.

The observed spread of meta-efficiency scores showed that some CT adopter efficiency scores were about 50%. These farmers follow CT recommendations only partially. For example, in the strict sense, CT expressed as conservation agriculture recommends the maintenance of crop residues on the soil surface as a mulch and minimizing tillage. Combined with a reduction in tractor fuel use, this can generate positive environmental externalities through carbon sequestration and offsetting CO_2 emissions. However, typically, partial adopters may not fully achieve above-mentioned emission mitigation outcomes that can be accrued with CT. Farmers using PBPs appear to occupy the largest share of farms at the frontier (43%), and the corresponding shares of PTOS and ST are 37% and 40%, respectively. The observed TT distributions appear to exhibit considerably more density in the smaller efficiency range than that of PBP, PTOS, and ST (Fig. 3C). The kernel density graph shows that farmers practicing CT can attain frontier efficiency with more ease (e.g., without having to make drastically significant changes in management practices and the inputs used) than TT. Among CT adopters, PBP farms perform slightly better—their densities cluster at higher efficiency levels, and the PBP curve advances at progressively higher rates of convergence to the EE frontier than other types of CT farms in the study area.

Nevertheless, on average, all CT technologies cluster around higher efficiency levels, illustrating that all the techniques appear to be environmentally superior to conventional TT. This was also confirmed by our equivalency testing of efficiency distributions using the adapted-Li test (Li et al., 2009), which reported a significant difference ($P < 0.001$) between CT and TT.

The technology gap ratio or meta-technology ratio (MTR) measures how close CT and TT farmers, respectively, are to the meta-technology frontier. The outcome for CT shows that on average, the MTR for CT is associated with a low technology gap with reference to the meta-technology frontier. The gap, however, is higher for TT. Thus, in the case of wheat production in our study areas, CT appears to be more promising—both technologically and environmentally. The MTR for ST and PTOS is 0.94, which means that ST and PBP farmers can produce about 6% more of the desired outputs that could be generated using the same inputs, though this requires that they employ the technology represented by the meta-frontier even after reducing 6% of GHG emissions. For PBP, the MTR is 0.99, which is very close to the meta-frontier, and is a fair representation of the meta-technology; i.e., the possibility for further improvement for farmers who have adopted this technology is very minimal. Conversely, the low MTR of TT, 0.72, represents a very inefficient technology; by shifting from TT to the meta-frontier technology (say, PBP), farms can reduce 28% of the observed rate of GHG emissions, potentially with an improvement of up to 28% in grain yield (Fig. 2).

Thirty percent of the farmers on the environmental efficiency frontier produced relatively low GHG emissions compared to farmers making use of TT (ca. 481 kg CO_2eq ha^{-1}). The corresponding GHG emissions under the various tillage options studied are given in Table 3. Although GHG emissions are expected to be relatively lower for farmers using CT, the amount of GHGs reduced by each different tillage and crop establishment practice provide a clearer picture of the trade-off between GHG emission and yield. PBP frontier farmers emit the lowest GHGs, but with lower yields than those achieved by farmers using PTOS. One of the reasons for the lower emissions rate observed for PBP may be attributed to the permanent or semi-permanent nature of some of the raised beds; upon which planting is carried out in each season such that no inversion tillage is required once the beds are established. Bed planting is also

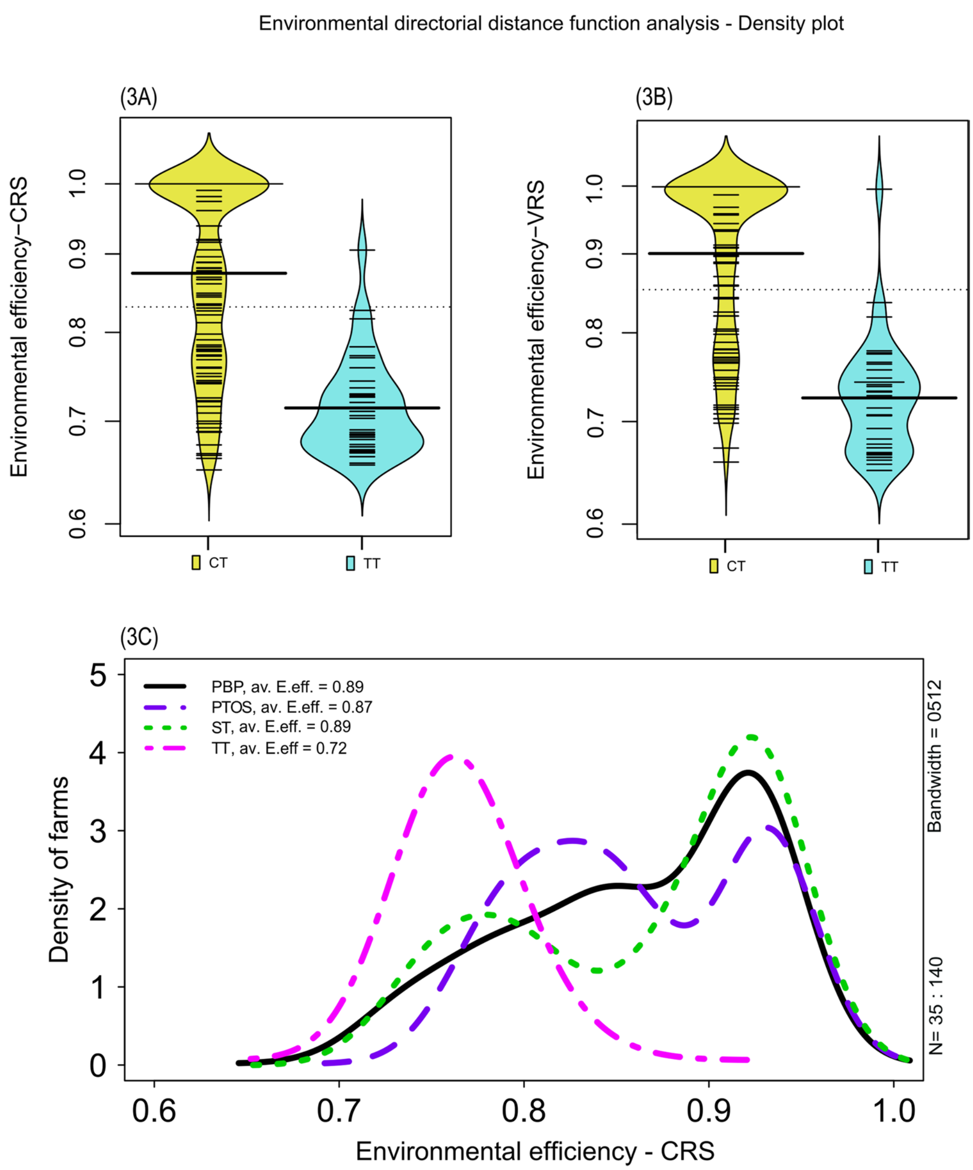

Fig. 3 Density plots showing environmental efficiencies of various tillage options. CRS and VRS indicate constant and variable returns to scale, respectively. CT and TT stand for conservation and traditional tillage. PBP, PTOS, ST indicate permanent bed planting, power tiller operated seeding, and strip tillage

Table 3 Meta-frontier farms, grain yield, and greenhouse gas (GHG) emissions. CRS and VRS indicate constant and variable returns to scale, respectively. CT and TT stand for conservation and traditional tillage. PBP, PTOS, ST indicate bed planting, power tiller operated seeding, and strip tillage

Tillage	Meta-frontier farms			Non-frontier farms		
	(%)[a]	GHG emissions of (Kg CO_2eq ha^{-1})	Grain yield (t ha^{-1})	(%)[a]	GHG emissions (Kg CO_2eq ha^{-1})	Grain yield (t ha^{-1})
PBP	43 (15)	316	4.44	57 (20)	437	3.87
PTOS	37 (13)	364	4.48	63 (22)	391	3.94
ST	40 (14)	396	4.06	60 (21)	398	3.61
CT	40 (42)	359	4.33	60 (63)	409	3.80
TT	0	–	–	100 (35)	481	3.68

[a]No of farms in parenthesis

typically associated with increased efficiency in irrigation. The absence of significant amounts of tillage once the beds are established reduces consumption of fuel, as does reduced irrigation water use that lowers pumping and hence fuel use. Of the three tillage options compared within CT technologies, an unexpected result that was observed is the higher emission from ST along with the lowest yield (Table 3). This appears to be resulted from our observations that for many of the ST farmers, input use is variable and also relatively low. As a result, farmers practicing ST were not on par with PBP or PTOS farmers in case of both emissions reduction and yield. Our results therefore indicate that whilst CT is associated with improved efficiencies, the environmental impacts across CT options are not necessarily similar.

Recent estimates of GHG emissions from wheat farms vary widely. In Researcher-led and managed, on-station trials carried out in Bangladesh, Rahman et al. (2021) reported an average emission of 2,028 kg CO_2eq ha^{-1} from conventional tillage. By contrast, in China, GHGs produced from wheat were almost two times higher (5,455 kg CO_2eq ha^{-1}) for wheat (Zhang et al., 2017). Such differences in range, however, can result from slight differences in coefficients used to calculate GHGs, as well as from methodological issues associated with measurement, and the difference in input rates applied to crops in fundamentally different climatic conditions that result in variation in the cropping season's length. Rahman et al. (2021) also found that soil organic carbon accumulation for CT practices were almost ten times (0.97–1.3 t ha^{-1}) than those achieved under traditional tillage (0.11 t ha^{-1}). . Unlike the studies mentioned above, which account for cumulative GHG emissions from all sources, our study estimated GHG emissions solely from primary and secondary sources of emission in South Asia's eastern Indo-Gangetic Plains of Bangladesh. Currently, approximately 0.82 million hectares is under conventional wheat cultivation in Bangladesh (BBS (Bangladesh Bureau of Statistics), 2020). At the same time, our estimates show that it is possible to reduce GHG emission by approximately 97 kg CO_2eq ha^{-1} through the use of CT technologies in Bangladesh. Although this is a relatively small amount compared to emissions that may result from other crops – particularly from rice – any reduction in GHGs that is associated with increased economic and agronomic productivity is arguably desirable from both a farmer and policy maker standpoint.

Factors determining the environmental efficiency of wheat farms

To obtain robust estimates in the FRM, the correct specification of the conditional expectation $E(\omega|x)$ of the dependent variable is validated using the specification tests proposed by Ramalho et al. (2010) (Table 4). Based on the specification tests, we chose complementary log–log (Clog-log) approaches for binary part and log–log specification for fractional part of our analyses (Table 5). The role of education in EE was found to be significant and positive for both adopters and non-adopters of CT technological options. The estimates of average partial effects show that efficiency improves by almost 3% when farmers have at least 10 years of formal education. At the same time, from the binary Clog-log FRM results, the probability of observing an efficient farmer in the study areas is also 2% higher for household farm heads with 10 years of education when compared to a less educated and/or illiterate household. However, within inefficient farms, the influence of education on efficiency gain is minimal. The importance of education in EE has already been demonstrated in the literature (Picazo-Tadeo et al., 2011). Educated farmers can often causally associate the positive influence of technology on environmental outcomes. In the study areas, on average, older farm household heads had only seven years of education on average, but younger farmers had at least 12 at the time of surveying. Thus, encouraging the younger generation to take up farming could potentially increase the EE of wheat farms in the study areas by approximately 1.2%, although efforts to retain youth in agriculture are beset with multiple challenges, most notably the appeal of working in other sectors that may be perceived as more 'advanced' or 'modern', and/or more remunerative. As reported before in Table 1, access to agricultural credit to assist in input provision does not delimit the adoption decision of CT wheat, while it appears to positively affect EE. The significant coefficient estimate (0.11) for this variable implies that formal or informal credit constraints have a large negative impact on efficiency. This also points to the benefits that may be accrued from improvement in access to financing to support the purchase of CT drills. On the other hand, access to other components of the crop management practices that may be required for well CT including improved seeds, balanced fertilizers, and methods for weed control, will also likely be necessary to improve the efficiency of inefficient adopters. Farmers exposed to training in conservation agriculture also appear to be more likely to adopt environmentally sound practices, as our results indicated a positive influence of training on households' capacity to cultivate wheat more efficiently.

The area of cultivable land owned by wheat farmers influences neither the likelihood of observing an efficient farm nor the efficiency of inefficient farms (Table 5). Gould et al. (1989) observed, on the other hand, that farm size is negatively associated with the adoption of soil conservation practices in tillage operations. We were constrained from testing the influence of the scale of operation on the efficiency of CT by the highly fragmented landholdings, very small farm size, and limited heterogeneity in acreage of cultivation. Other household variables—including farmers' ages, household sizes, and off-farm income—presented no statistically significant coefficients, whereas the remoteness of the village was found to be associated with observing an inefficient farm. The negative impact of remoteness on efficiency could be associated with transportation difficulties that may be encountered in moving CT machinery or inputs to the farm, as well as with possible challenges in accessing advice from extension workers. However, in the sample villages, the average distance from the nearest extension office to farms on which CT had been at least partially adopted farms was only 14 km, and most of these farms have good road access. The importance of extension, credit, and asphalted roads have been shown to increase both cropping intensity (Aravindakshan et al., 2020) and Bangladeshi farmers' preference for sustainable crop management techniques (Aravindakshan et al., 2021a; b. On the other hand, on more remote farms, a higher share of the households lack access to extension advice, and farmer-to-farmer information flows are more prevalent. Furthermore, private agro-input dealers are sought out by farmers more often than formal extension services. This is a common observation in Bangladesh, representative of a risk that may decrease efficiency and that introduces a moral hazard, as private agrcultural input dealers may be biased towards intensive input use in order to encourage sales. Efforts are therefore needed to educate agricultural input dealers on the long-term business risks associated with inappropriate marketing or the provision of mis-information to farmers in ways that may increase their profitability in the short-term, but which undermines farmers' efficiency and may encourage distrust among their farmer-clients in the long-run, in addition to contributing to negative environmental outcomes.

Although a range of fertilizer types was used by the farmers in our study, the quantity of nitrogen applied between adopters and non-adopters of CT practices was more or less similar (Table 1). Therefore, the variation in the residual effect of nitrogen on inefficiency and GHG emissions across efficient and inefficient farms is likely have arisen less from fertilizer management but more from fertilizer application timing. The application of nitrogen in splits before irrigation

Table 4 Specification test probability values for two-part fractional regression model (FRM) based on DDF

	Binary component				Fractional component			
	Logit	Probit	Loglog	Cloglog	Logit	Probit	Loglog	Cloglog
RESET (Regression Equation Specification Error) test	0.360	0.370	nc	0.377	0.151	0.059*	0.297	0.012*
GGOFF (Generalized Goodness-of-functional Form) - I test	0.341	0.414	nc	0.451	0.073*	0.063*	0.204	0.012*
GGOFF (Generalized Goodness-of-functional Form) - II test	0.452	0.341	nc	0.451	0.124	0.046*	0.204	0.012*
P-test								
H0/H1:FRM-Logit	na	0.989	nc	0.278	na	0.248	0.134	0.173
H0/H1:FRM-Probit	0.155	na	nc	0.175	0.105	na	0.261	0.056*
H0/H1:FRM-Loglog	nc	na	na	nc	0.069*	0.058*	na	0.266
H0/H1:FRM-Cloglog	0.830	0.999	nc	na	0.015*	0.012*	0.113	na

** and * denote test statistics which are significant at 5% or 10%, respectively

na indicates not applicable, *nc* non-convergence of the model due to out of bound estimates in "*R*"

Table 5 Determinants of environmental efficiency in wheat farming as observed under the fractional regression model (FRM)

Dependent variable: meta-frontier environmental efficiency scores (CRS) by directional distance function estimation	Two part FRM: model estimates		Two part FRM: average partial effects
Independent variables	Binary Cloglog ($n=140$)	Fractional Loglog ($n=98$)	Binary Cloglog + fractional Loglog
Model intercept	−4.676***(1.355)	1.138***(0.222)	
Cultivable land owned	−0.275(0.414)	−0.040(0.059)	−0.042(0.060)
Remoteness	−2.752**(0.014)	−0.037(0.084)	−0.400***(0.152)
Distance to the nearest extension office	−0.022*(0.013)	−0.001(0.003)	−0.003*(0.002)
Education of the farmer	0.211***(0.053)	0.045***(0.017)	0.033***(0.006)
Age of the farmer	0.006(0.016)	0.000(0.003)	0.001(0.002)
Training on conservation tillage	0.468**(0.216)	0.133(0.090)	0.074**(0.030)
Access to credit	0.782**(0.390)	−0.078(0.085)	0.109**(0.054)
Involvement in farming	0.829**(0.407)	−0.021(0.070)	0.119**(0.057)
Household size	0.028(0.113)	−0.006(0.013)	0.004(0.016)
Off − farm income	−0.004(0.009)	0.001(0.002)	−0.001(0.001)
Advice from input dealer (numbers)	−0.590(0.388)	−0.128(0.122)	−0.092*(0.055)
Experience in conservation tillage	0.120(0.079)	0.001(0.021)	0.018(0.011)
Nitrogen fertilizer application before irrigation	0.757**(0.362)	0.030(0.096)	0.111**(0.50)
NPK fertilizers application in splits	0.622*(0.373)	0.127(0.095)	0.090*(0.048)
Occurrence of Nitrogen fertilizer application delay	−0.011(0.460)	−0.343***(0.104)	−0.020(0.062)
Awareness on soil and water conservation	0.294(0.413)	0.006(0.090)	0.043(0.060)
	R^2: 0.352	R^2:0.238	

is found to affect efficiency positively (Table 5). The efficiency impact of the time of application of nitrogen was however even more pronounced, As the date of nitrogen application is progressively delayed, our observations suggested that efficiency drops drastically. In the rice–wheat systems of South Asia, the general recommendation is to apply nitrogen fertilizer to wheat in at least two split doses at planting, and at crown root initiation) stages, although an additional split at maximum tillering or heading may also be suggested. Apart from split application of fertilizer, the right type of fertilizer that is applied both at the right rate (quantity) and right time, and right place of the plant (e.g. active root zone) is necessary to increase nutrient uptake and reduce the risk of environmental losses and emissions from fertilizer application (Bindraban et al., 2015).

Even where farmers have adopted at least three splits for nitrogen application, some may broadcast nitrogen quite late into the season (Singh et al., 2013). Our results indicate that households (66% of them in the sample) applying nitrogen at maximum tillering stage are more environmentally efficient than those who apply after this stage. A recent agronomic study by Singh et al. (2013) among wheat farmers in South Asia also reported that the impact of an additional dose of nitrogen at maximum tillering stage can significantly improve yield. The intensity of production-emission trade-offs in wheat therefore not only depends on the quantum of inputs (e.g., the rate at which fertilizers are applied) but also on the schedulingof input application. Considering other variables, although a positive impact of farmers' awareness on soil and water conservation techniques on environmental efficiency is generally expected, the variable presented no statistical significance in the fractional regression model. This is despite our observations that CT adopters had more awareness on soil and water conservation than TT farmers (Table 1). CT adopters nonetheless were found to have saved approximately 373.0 m^3 ha^{-1} of irrigation water, on average, and almost consumed 27% less than their TT counterparts (Table 1). Although we did not observe statistical differences, this suggests that further increased efficiency under CT could be encouraged by extension services that capitalize on CT adopters' tendency towards improved soil and water management practices (Table 5).

CT adopters saved approximately 37% of the fuel used by tractors and irrigation pumps compared to non-adopters. This is consistent with the estimates by Aravindakshan et al. (2015), who reported > 30% fuel savings for CT wheat in Bangladesh. Considering the number of tillage passes and fuel use efficiency for land preparation and crop establishment, CT was associated with a reduction in tillage frequency (< 2 passes for CT, with bed planting being the only practice that may require more than one tillage event, compared to 3–5 passes for TT techniques). Our data suggest that the corresponding improvements in environmental efficiency can approach approximately 23%, 21%, and 23% for PBP, PTOS, and ST adopters relative to traditional, multi-pass tillage practices.

Conclusions

The significance of climate change mitigation strategies in cereal production in South Asia's major rice–wheat producing regions points to the importance of research that rigorously evaluates different crop management practicesincluding comparison and contrasts between alternative tillage and crop establishment systems. This paper investigated the environmental efficiency of various tillage production systems on wheat farms in three regions within Bangladesh by incorporating the GHG emissions in the DDF model. We also explored the underlying factors affecting the environmental efficiency using fractional regression modeling. These techniques provide a range of insights that are important and would otherwise be challenging to observe under formal agronomic experimentation.

Firstly, optimizing environmental performance requires farm-specific strategies, including responses to policies that encourage the appropriate use of CT practices. Such farm policies require addressing two types of heterogeneity, including environmental-economic efficiencies of the production process within different CT tillage configurations, and also within farms and farmers. The environmental efficiency of conservation tillage in our study was found to be 88%, and was significantly greater than that observed with farmers practicing conventional tillage (72%). Secondly, our study showed that the impact of heterogeneities in tillage technologies in CT does not significantly influence the environmental–economic efficiency of the production process. Farm policies may fail to address the differential impact of tillage that arises from within and between farm and farmer heterogeneities. Thirdly, nutrient management was found to have particularly important ramifications for environmental efficiency improvements. Efforts are required to aid farmers to make better decisions on fertilizer application and reduce nutrient losses (Rodriguez, 2020). Focused extension and awareness raising programs could help to improve farmers' nutrient management practices, specifically the timing of N fertilizer splitting. Thirdly, the level of farmers' education plays a clear role in efficiency and is reflected in our model outcomes. Adopting PBP, ST, and PTOS leads to comparatively lower GHG emissions, and savings in fuel use. The ways in which improved efficiency can be obtained with reduced use of fuel may in particular render these practices of interest to resource-constrained, smallholder farmers, but as our study shows, they may still require access to finance to aid in the acquisition of CT machinery services and some inputs. These results are particularly important because around 60% of the farms in our sample were small and marginal farms, or were managed by landless farmers facing severe resource constraints. Despite this, our efficiency estimates indicate that due to over-use of inputs and other resources, TT farmers have around 30% greater negative environmental impacts in the form of GHG emissions than CT farmers. Thus, an appropriate strategy would be to optimize resource use without compromising yield, and to improve farmers' net benefits by reducing production costs.

Since we relied on GHG emissions that were computed from coefficients for primary and secondary sources of input management, we were not able to account for emissions from soil, nor were we able to consider soil carbon sequestration. Agronomic experiments could therefore be used to further assess and potentially validate our findings in the different districts of Bangladesh under which studies were undertaken. Finally, in our efficiency model, social and institutional constraints to wheat production were not explicitly examined. However, instead of directly introducing these constraints in the DDF model, we tested important key constraints in the second stage FRM.

Environmental externalities may not always be considered and internalized in agricultural production. A way to cope with this market failure could be to internalize the provision of further positive environmental outcomes by compensating farmers for practices that sustain ecosystem services and that reduce pollution. In addition, our study highlights the ways in which farmers and the environment could benefit from improvements in input management under both TT and CT options. Considering the comparatively high environmental outcomes associated with CT and its reduced cost of cultivation, mechanisms should be explored to increase farmers' ability to access CT machinery services – particularly for marginal and resource-poor farmers – on an affordable cost for tillage and crop establishment services.

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Author contribution Sreejith Aravindakshan, Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – Original draft, Writing — review and editing, and Data visualization.

Ali AlQahtany, Methodology, Software, Validation, Writing — review and editing, and Data visualization.

Muhammad Arshad, Conceptualization, Investigation, Project administration, and Writing — review and editing.

Manjunatha A.V., Methodology, Writing — review and editing, and Data visualization.

Timothy J. Krupnik, Secured funding, Management, Conceptualization, Methodology, Writing – review and editing.

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We the authors of the manuscript titled "A metafrontier approach and fractional regression model to analyze the environmental efficiency of alternative tillage practices for wheat in Bangladesh" provide the following declarations, which is true to the best of our knowledge and belief.

Declarations

Disclaimer The contents and opinions expressed herein are those of the authors and do not necessarily reflect the views of USAID, BMGF, EC, FSE, WUR, or ZALF.

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