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Eco-efficiency of high-yielding variety rice cultivation after accounting for on-farm environmental damage as an undesirable output: an empirical analysis from Bangladesh*

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This study computes the eco-efficiency of high-yielding variety (HYV) rice production by including an on-farm environmental damage index (OFEDI) as an undesirable output using data envelopment analysis. It then identifies its determinants by applying an interval regression procedure on a sample of 317 farmers from north-western Bangladesh. Results reveal that the mean level of the OFEDI-adjusted production efficiency (i.e. eco-efficiency) is 89 per cent, whereas ignoring OFEDI adjustment (i.e. with OFEDI = 0) reduces the mean level of efficiency to 69 per cent, implying that the production of undesirable output or on-farm environmental damage induces an efficiency loss of 20 per cent with significant differences across regions. The proportion of farmers' income from HYV rice agriculture, land ownership, extension services and socio-environmental living standard are the significant determinants of improving eco-efficiency. Policy implications include investments in extension services and land reform measures to increase land ownership, which will synergistically improve eco-efficiency of HYV rice production in Bangladesh.

Key words: Bangladesh, data envelopment analysis, eco-efficiency, environmental damage, high-yielding variety rice agriculture, undesirable output.

1. Introduction

Increasing the level of efficiency in agricultural production has been an important policy objective in most agrarian economies. Agricultural practices that aim to increase production efficiency are conditional upon limiting their adverse impacts on the farm environment. This situation arises because growth in agricultural productivity and its sustainability primarily depend on the quality and efficient management of the natural resource (capital). Korhonen and Luptacik (2004) indicated that the environmental impacts (undesirable output) are jointly produced with the desirable output of a

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production activity. As such, undesirable output should be incorporated into the economic analysis of the production performance of firms. In this respect for a natural resource-depleting production activity such as agriculture, it is important to evaluate an environmentally adjusted measure of production efficiency at the farm level, that is eco-efficiency of agricultural farms.

Evaluating eco-efficiency in agriculture is challenging. The challenge lies in defining and formulating an indicator that can measure the overall impact on farm environment (Binder and Feola 2010), because an indicator should incorporate agricultural multifunctionality. While addressing agricultural multifunctionality, most studies have considered two aspects of agriculture in their evaluation process, that is farming practice-related indicators and/or farming system-related indicators (López-Ridaura *et al.* 2005). Some studies have chosen agricultural emission-related environmental attributes only (Rigby *et al.* 2001). In addition to these, farmers' environmental awareness/perception of agricultural pollution has also been indicated as an important socio-environmental aspect of agriculture in certain agroecological studies (Rahman 2005). Zhen and Routray (2003) additionally emphasised analysing country-specific agri-environmental aspects in addressing environmental sustainability and highlighted that developing countries would face greater challenges in this respect than those faced by developed nations. It is also worth noting that incorporating farming system (or state)-related, farming practice-related and farmers' perception-related environmental impacts into a composite mode would be useful for evaluating eco-efficiency. In previous studies, the inefficiency arising due to on-farm environmental impacts has rarely been segregated econometrically in farm-level efficiency analyses (Picazo-Tadeo *et al.* 2011; Berre *et al.* 2015) because of the challenge of incorporating all attributes into its measurement.

Given this backdrop, the principal aim of this study was to evaluate on-farm eco-efficiency in relation to high-yielding variety (HYV) rice production by incorporating an on-farm environmental damage index (OFEDI) as an undesirable output alongside the desirable output to measurement production efficiency of a farm. We achieve these aims by first estimating production efficiency of the farms ignoring any environmental damage (i.e. assigning zero values to the OFEDI) and then re-estimating the model by adjusting with nonzero OFEDI values for the same set of farms. Theoretically, the first model is a conventional production efficiency model because the OFEDI is assumed to hold zero values which need to be adjusted to obtain the measure of eco-efficiency. Technically, the eco-efficiency estimate explains true production efficiency of a given farm when all of the farm's undesirable outputs are minimised, and the gap between the OFEDI-adjusted production efficiency (eco-efficiency) and the production efficiency with OFEDI = 0 evaluates the environmental impact-induced loss of production efficiency for a given farm. The main contribution of our study to the existing agroecological and/or productivity and efficiency literatures is that we have applied a comprehensive measure to evaluate on-farm environmental impacts caused by a given agricultural operation (i.e. HYV rice production) using a set of 17 indicators selected and constructed from three main domains of impacts, that is means-based impacts (MBI), effect-based impacts (EBI) and perception-based impacts (PBI) (see Sections 2 and 3.1 for details on the critique of existing approaches and the construction of our measure, respectively).

The remainder of the study is organised as follows. Section 2 provides a comprehensive review of the range of eco-efficiency concepts and measures. Section 3 presents the methodology, analytical framework and the data. Section 4 presents the results. Section 5 provides conclusions and draws policy implications.

2. Eco-efficiency: a brief review of concept and measures

A variety of criteria have been used to explain the concept of eco-efficiency once it was recognised as a useful operational tool for sustainability analysis (Fritsch 1995). Operational research on environmental management suggests a number of alternative terminologies for defining the environmental impact indicators to evaluate eco-efficiency. Most of these studies on environmental efficiency have defined and formulated environmental impact indicators as a denominator of measuring eco-efficiency. In agroecological studies on environmental efficiency, the notion of eco-efficiency is frequently explained in terms of agricultural aspects. In this context, the eco-efficiency denominator is usually denoted as the 'undesirable output' (Seiford and Zhu 2002; Amirteimoori *et al.* 2006). Picazo-Tadeo *et al.* (2011) analysed farming practice-related impacts to define the undesirable output variable and incorporated it into their proposed model of environmental efficiency. Graham (2009) considered effect-based (or farming state-related) environmental impacts to evaluate the eco-efficiency of chemical fertiliser application on ground and surface water. Many studies have assessed on-farm soil nutrient balance as an indicator of environmental damage in defining undesirable output factor in environmental efficiency models (e.g. Hoang and Alauddin 2012). Most of these studies formulated the undesirable output component using data from secondary sources.

Pollution data relating to on-farm environmental attributes are often unavailable from secondary sources. Consequently, primary data on farm-level environmental impacts are more useful in addressing agriculture-environment issues, particularly for agriculture-based developing countries. Environmental impact indicator accounting usually requires reconciling relevant dimensions and aspects of a given production process within the context of a given country. Specifically, an eco-efficiency measure that incorporates important aspects of on-farm environmental damage in terms of an index could be effectively used as an operational tool to assess and address agricultural sustainability.

3. Methodology and data

3.1 On-farm environmental damage index: the undesirable output

This study measures the extent of farm-level environmental damage by aggregating several indicative environmental impact variables (Girardin *et al.* 1999; Bockstaller and Girardin 2003) to construct an OFEDI. The proposed index incorporates three separate types of indicative variable groups: (i) production practice-related (means-based), (ii) system (or state)-related (effect-based) and (iii) farmers' perception-related (perception-based) environmental impacts. A statistical additive aggregation method was utilised to compile and add these various indicators to produce a composite index as follows (Sabiha *et al.* 2016):

$$\mathrm{OFEDI}_i = \sum_{m=1}^{n} M_m + \sum_{e=1}^{k} E_e + \sum_{p=1}^{l} P_p, \qquad (1)$$

where OFEDI_i = on-farm environmental damage index of the ith farmer/farm; M_m = means-based indicators; E_e = on-effect-based indicators; P_p = perception-based indicators.

This study selected indicators that are relevant to the effects of by HYV rice farming on the environment and are widely recognised in agroecological studies (Alauddin and Hossain 2001; Rahman 2005). A list of means-based and effect-based environmental impacts was prepared using previous literature on Bangladesh rice agriculture and environmental impacts. To select the PBI, several (nine) focus group discussions (FGD) (with the HYV rice farmers) were conducted prior to the field survey. We then finalised the PBI by selecting those that were mostly experienced/faced by HYV rice farmers while cultivating HYV rice during the previous crop year. Table 1 presents the details of the measurement methods and formulas used to construct these indicators. All raw data were scaled to a normalised score ranging from 0 to 1 using an optimal range scoring function (Rahmanipour *et al.* 2014), where scores close to 1 imply a stronger environmental impact of a given variable. The OFEDI is then formulated using these normalised values in Equation (1) for each production unit (i.e. HYV rice farms). Thus, the constructed OFEDI is defined as the index of undesirable output produced by HYV rice farms which is then subsequently added as a variable to compute eco-efficiency. A high OFEDI implies a high level of environmental damage. For more details on the construction procedure, see Sabiha *et al.* (2016).

We illustrate our approach empirically by utilising data from a survey of 317 HYV rice farmers of northern Bangladesh, where, over the past few decades, the environment and natural resources of have been affected in part by agricultural pollution caused by the widespread use of HYV seeds in cereals, that is rice, wheat and maize (Alauddin and Hossain 2001). Farm-level studies have demonstrated that Bangladesh is experiencing a decline in

Table 1 On-farm environmental damage index (OFEDI): variable description

Indicative variables	Method	Formula
Means-based impacts (MBI)		
Crop concentration index (CCI)	Herfindahl index of crop concentration	HI $= \sum \alpha_j^2,\ 0 \le \mathrm{HI} \le 1$; α_j = area share occupied by the jth crop in A. A value of 0 denotes perfect diversification, and a value of 1 denotes perfect concentration
Soil stress factor (SSF)	Optimal range scoring function: MBF	$f(x) = 0.9\left(\frac{x-2}{36-2}\right) + 0.1$ Hypothetical threshold range 2–36. (see Appendix I)
Nitrogen risk factor (NRF)	Applied dose (NA)/ recommended dose (NR). Optimal range scoring function: MBF if NA > NR	$f(x) = 0.9\left(\frac{x-1.01}{2.0-1.01}\right) + 0.1$ Hypothetical threshold range is 1.01–2.0
Effect-based impacts (EBI)		
Soil pH (SpH), surface water pH (SWpH), ground water pH (GWpH)	Optimal range scoring function: LBF if pH < 7	$f(x) = 1 - 0.9\left(\frac{x-4.0}{6.9-4.0}\right)$ Scientific threshold range is 4.0–6.9, if pH < 7
	MBF if pH > 7	$f(x) = 0.9\left(\frac{x-7.05}{8.5-7.05}\right) + 0.1$ Scientific threshold range is 7.05–8.5, if pH > 7
Soil salinity (SSL)	Optimal range scoring function: MBF	$f(x) = 0.9\left(\frac{x-0.2}{2.0-0.2}\right) + 0.1$ Scientific threshold range is 0.2–2.0 ds/m
Soil compaction (SCM)	Optimal range scoring function: MBF	$f(x) = 0.9\left(\frac{x-100}{500-100}\right) + 0.1$ Scientific threshold range is 100–500 psi

Perception-based impacts (PBI)

Soil fertility problem (SFP); soil water holding capacity problem (SWH); water logging (WLG); water depletion (WDP); soil erosion (SER); pest attack problem (PAP); crop diseases problem (CDP); health impact; reduction in fish catch (RFC).

Five-point Likert scale using agree – disagree approach

Likert scale scoring for perception-based indicators

	Disagree			Agree		
Impact Interpretation	None	Very low	Low	Medium	High	Very high
Impact Weights (Indicator values)	0	0.2	0.4	0.6	0.8	1.0

Note MBF means 'more is bad for the environment function'; LBF means 'less is bad for the environment function'; x is the indicator's actual value; $f(x)$ is the indicator's derived impact score, where for every indicator score, the value range is $0.1 \le f(x) \le 1$.

the production efficiency of rice over time (Salim and Hossain 2006; Alam *et al.* 2011) and decreasing returns to scale (Rahman 2011), which could be explained by the extent of agricultural pollution and environmental factors. In addition, farmers have shown awareness of environmental impacts such as soil and water problems due to cultivating HYV rice in Bangladesh (Rahman 2005). This provides an opportunity to measure the extent of the environmental impacts generated at the farm level that could explain the observation of a low and/or declining level of technical efficiency in HYV rice cultivation.

We hypothesise that, in any region or in any farm, if one or several environmental impacts are absent, the associated indicators will hold a normalised score of 0. Other impacts might generate nonzero values of the normalised scores for these specific regions or farms. We have taken the cumulative form of the normalised scores of these impacts. We did not weight individual environmental impacts because we assumed that all these impacts are equally important. The farmers during the FGD sessions also assigned high importance to these impacts.

3.2 Incorporating undesirable output into the eco-efficiency model

Eco-efficiency, which involves the idea of producing maximum outputs using minimum inputs while reducing on-farm environmental impacts, could provide important information for decision-making vis-à-vis improving environmental performance. Many researchers have recommended the use of data envelopment analysis (DEA) to measure the eco-efficiency of a given production activity (e.g. agriculture) (Poit-Lepetit *et al.* 1997; Hoang and Alauddin 2012). DEA not only allows for the measurement of environmental efficiency but also examines the nature and causes of environmental inefficiencies (i.e. bad environmental performance) (Tyteca 1996). Korhonen and Luptacik (2004) noted that DEA provides an in-depth insight into the causes of eco-inefficiencies when a pollutant is included as an undesirable output in an analysis. Cooper *et al.* (2011) identified that DEA could successfully reduce errors in efficient frontier estimation. Therefore, estimating eco-efficiency by applying DEA can effectively summarise different environmental impacts and allow decision-making units to arrive at an environmentally sustainable production decision, as performed in this study. Generally, three categories of factors, that is desirable outputs, undesirable outputs (i.e. environmental impacts) and inputs, are considered when formulating a DEA model intended to evaluate environmental performance (Cherchyey *et al.* 2013).

This study proposes an efficiency model that assumes that there are I homogeneous farms (i.e. HYV rice farms) consuming J inputs for producing outputs R (i.e. HYV rice grown in three seasons: Aus (premonsoon), Aman (monsoon) and Boro (dry winter). The outputs corresponding to indices $\{1...Z\}$ are desirable (good) outputs, and the outputs corresponding to indices $\{Z + 1, Z + 2, \ldots R\}$ are undesirable (bad) outputs, that is MBI, EBI and PBI (Table 1). These undesirable output indices correspond to the OFEDI when aggregated cumulatively using Equation (1). The proposed efficiency model (Eqn 2) represents all outputs as a positive weighted sum and uses negative weights for undesirable outputs. The model assumes that the ith farm produces y_{ri}^{g} units of desirable output (i.e. the HYV rice) and y_{si}^{b} units of undesirable output (i.e. the OFEDI) using x_{ji} units of jth input.

First, we estimate the ECE model without adjusting the undesirable output as expressed by Equation (2) (i.e. assuming OFEDI = 0 values for all farms). It is worth mentioning that assuming OFEDI = 0 does not mean HYV rice cultivation is releasing zero (no) environmental impact, rather it means the model is not identifying any environmental impacts. Theoretically this efficiency score can be considered conventional production efficiency (denoted as $\mathrm{ECE_{D0}}$). We then run a separate DEA that measures eco-efficiency ($\mathrm{ECE_{D+}}$), by assigning nonzero values of the OFEDI (the index of undesirable outputs) to the same ECE model (Charnes *et al.* 1994; Korhonen and Luptacik 2004). Other outputs (rice) and inputs are of the same type and number as before. Thus, we consider equal numbers and the same types of inputs and outputs for both versions of the ECE. Therefore, solving Equation (2) twice in this manner would result in a pair of efficient frontiers that measure $\mathrm{ECE_{D0}}$ and $\mathrm{ECE_{D+}}$ scores. Because $\mathrm{ECE_{D0}}$ can be considered as the conventional production efficiency (without adjusting environmental damage) and $\mathrm{ECE_{D+}}$ eco-efficiency (with adjusting for environmental damage), the loss of production efficiency due to agricultural pollution can be explained by analysing the gap between these two efficiency frontiers ($\mathrm{ECE_{D0}}$ as the lower bound and $\mathrm{ECE_{D+}}$ as the upper bound).

The use of an undesirable output as an index to measure eco-efficiency is reported in a number of DEA studies (e.g., Amirteimoori, et al., 2006; Picazo-Tadeo, et al., 2011; Hoang and Alauddin, 2012). Seiford and Zhu (2002) noted that when an undesirable output is incorporated into the eco-efficiency model, the efficiency level will be higher than the efficiency measure that does not incorporate any undesirable output (e.g. environmental impact). The model we adapted in our study was explained by Korhonen and Luptacik (2004). Equation (2) is essentially a standard input-oriented DEA, provided that the undesirable outputs behave like inputs such that the HYV rice farms simultaneously reduce inputs and undesirable outputs to increase eco-efficiency (ECE) (Seiford and Zhu 2002; Amirteimoori *et al.* 2006). In this study, an input-oriented constant return to scale multistage DEA was applied to run the $\mathrm{ECE_{D0}}$ and $\mathrm{ECE_{D+}}$ versions of the basic ECE model using DEAP 2.1 software (Data Envelopment Analysis Program) written by Professor Tim Coelli, Centre for efficiency and Productivity Analysis (CEPA), University of Queensland, Australia.

3.2.1 Basic ECE model

$$\begin{aligned}
&\max \mathrm{EcoE}_o = \frac{\sum_{r=1}^{Z} \mu_r y_{ro}^{g} - \sum_{s=z+1}^{R} \mu_s y_{so}^{b}}{\sum_{j=1}^{J} v_j x_{jo}} \\
&s.t. \frac{\sum_{r=1}^{Z} \mu_r y_{ri}^{g} - \sum_{s=z+1}^{R} \mu_s y_{si}^{b}}{\sum_{j=1}^{J} v_j x_{ji}} \leq 1, \\
&\{i = 1, 2, \ldots I\} \\
&\mu_r, v_j \geq \varepsilon, r = 1, 2, \ldots z; j = 1, 2, \ldots J \\
&\varepsilon > 0 \,(\text{non - negativity})
\end{aligned} \quad . \tag{2}$$

3.2.2 Determinants of eco-efficiency: an application of interval regression model

An interval regression model is used when the interval within which each observation of the outcome variable falls is known although the exact value of the observation remains unknown (Manski and Tamer 2002). This study used the interval regression model to identify the determinants of the expected level of eco-efficiency because there are two sets of observed efficiencies for a given HYV rice farm: (a) the $\mathrm{ECE}_{\mathrm{D0}}$ at which the undesirable output component holds zero value y^{b0}, which is to be subtracted or adjusted from the desirable one and defines the lower bound of the expected eco-efficiency, and (b) the $\mathrm{ECE}_{\mathrm{D+}}$ at which the undesirable output component holds some positive value y^{b+}, which is to be subtracted or adjusted from the desirable one and defines the upper bound of the expected eco-efficiency. The model was fitted using DEA, a relative performance measurement approach that analyses best practice frontiers and hence measures relative efficiencies instead of the actual efficiency. Therefore, it is hypothesised that the expected value of eco-efficiency for a given HYV rice farm would lie within these threshold efficiency values derived from $\mathrm{ECE}_{\mathrm{D0}}$ as a lower bound and $\mathrm{ECE}_{\mathrm{D+}}$ as an upper bound.

Among the latent variable interval regression models, this study employed the following linear model as applied by Stewart (1983):

$$y_i^* = X_i \beta + \varepsilon_i, \tag{3}$$

where only the interval threshold (i.e. $\mathrm{ECE}_{\mathrm{D0}}$ and $\mathrm{ECE}_{\mathrm{D+}}$) containing the dependent variable y_i^* (expected eco-efficiency) is observed, X_i denotes a vector of explanatory variables and ε_i are independently and identically distributed random disturbances. If all possible realisations of y are partitioned into J different intervals, then we observe that $y_i = j$ if

$$A_{j-1} \leq y_i^* \leq A_j, \tag{4}$$

where A_{j-1} and A_j are the lower (ECE_{D0}) and upper (ECE_{D+}) thresholds, respectively, for the *i*th farm. Eight explanatory variables were selected to explain the expected eco-efficiency of a given HYV rice farm: farmers' education, age, access to extension services, HYV rice cultivation experience, land ownership, share of income from HYV rice agriculture in total income, number of earning members and socio-environmental living standard. This choice of variables is justified as follows.

Farmers' education, age, access to extension services and cultivation experience are hypothesised to be directly related to improving the expected eco-efficiency and productivity of rice cultivation (Rahman and Salim 2013). The land ownership status and agricultural income share of the HYV rice farmers are considered two important factors that could help achieve the expected level of eco-efficiency (Alam *et al*. 2011). The share of earning members in the family as a proxy for subsistence pressure could also be used to explain the expected eco-efficiency because increasing the proportion of earning members would potentially reduce the subsistence pressure, which in turn would positively influence eco-efficiency. As an indicator of environmental consciousness, farmers' living standard is emphasised in this study, with the indicator analysed in terms of a household pollution index (Estoque and Murayama 2014). Farmers who use environmentally friendly energy sources for household use, properly dispose of household waste, and use a healthy sanitation system and sources of pure water for drinking, are assumed to be conscious of environmental pollution. Such socio-environmental living standards (see Appendix II for construction details) would not only reflect farmers' environmental consciousness but also help realise the expected level of eco-efficiency in farm production.

3.3 Study area and the data

Primary data on the production and environmental impacts of HYV rice agriculture were collected by conducting a survey in three north-western regions of Bangladesh, that is Rajshahi, Pabna and Natore regions, which are generally suitable for HYV rice cultivation. Climate conditions and physiographic characteristics are similar among these regions (Figure 1). These regions belong to physiographic unit 8, that is the Ganges River Floodplain, which is identified as suitable for crops and has no major cultivation difficulties (Alauddin and Hossain 2001). The agroecological zones that belong to these regions comprise land levels that are mostly suitable for irrigation-fed HYV crops (e.g. rice and wheat). Most parts of these regions have neutral to slightly reactive soil properties and silty clay loams, which are favourable to rice cultivation. HYV rice is cultivated as one of the major grains in these regions, with the share of cultivation growing in these regions over the past five crop years (Bangladesh Bureau of Statistics: BBS 2009-13, Annual Reports on Estimates of Bangladesh Rice Crop).

Three unions from each of these regions were randomly chosen to select farm households. The list of registered rice farm households was collected from the respective Union Agriculture Extension Offices. Next, a random sampling procedure was used to select 317 HYV farm households for the survey. The sample size was calculated following the method reported by Bartlett *et al.* (2001). The survey was conducted to investigate the extent of environmental impacts of HYV rice cultivation for the crop year October 2012 to September 2013. The first author organised and conducted the survey with graduate students of Rajshahi University using face-to-face interviews. The survey was conducted from October 2013 to December 2013.

4 Results

4.1 Summary statistics of the variables

Table 2 describes the data on production factors used for modelling ECE_{D0} and ECE_{D+} and the summary statistics of the farmers' socio-economic and socio-environmental attributes. Table 3 presents the environmental impact values, which are the normalised scores of the raw values collected during the survey. On average, farms of the Rajshahi region produce HYV rice output valued at BDT[1] 137,292 per hectare of land, whereas the OFEDI (the

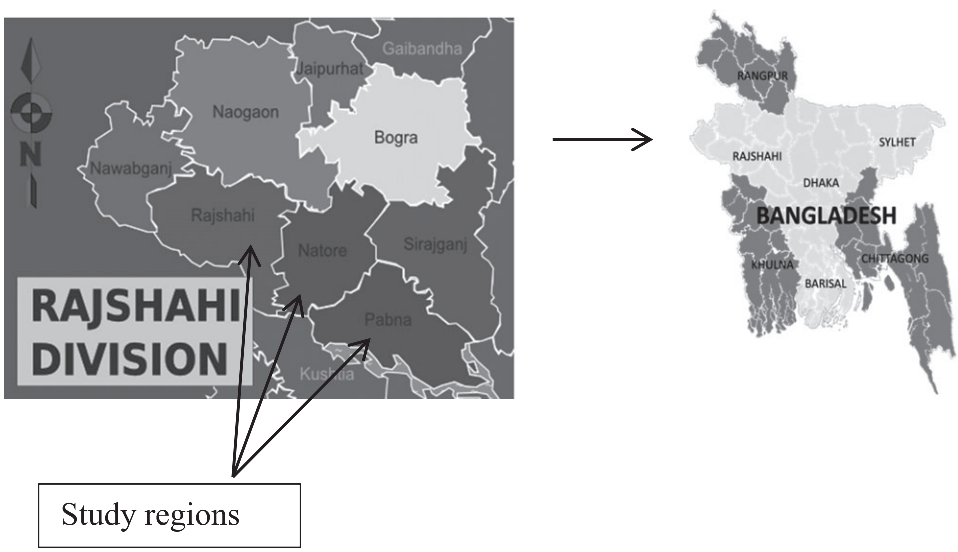

Figure 1 Map of the survey areas.

[1] BDT is the currency of Bangladesh. USD 1 is equivalent to 78.25 BDT (on 27 January 2016).

Table 2 Mean values of inputs, outputs, determinant variables

Name and description	Rajshahi	Pabna	Natore
AGE (Age (years))	47.46	52.65	46.24
EDU (Education: schooling years)	6.52	7.08	7.86
EARN (Proportion of earners in the family)	0.68	0.71	0.67
AGIN (Agriculture-income share: income from high-yielding variety (HYV) rice agriculture/total income from other agriculture and off farm per month)	0.67	0.71	0.53
EXP (HYV rice cultivation experience years)	14.3	15.3	14.9
EXTN (Extension service taken in last crop year (1 if yes; 0 otherwise))	0.11	0.30	0.192
LNDW (Share of self-owned land: self-owned/total land holdings)	0.90	0.99	0.79
SELI (Socio-environmental living index)	0.74	0.79	0.71
Desirable output value (BDT per hectare)	137,292	149,556	145,293
Chemical fertiliser (kg per hectare)	583	447	548
Pesticide (kg per hectare)	11	9	14
Irrigation cost (BDT per hectare)	13,951	11,257	15,694
Seed cost (BDT per hectare)	15,445	3774	4151
Tilling cost (BDT per hectare)	6059	4123	6187
Labour cost (BDT per hectare)	40,467	35,814	47,116
Land rental value (BDT per hectare)	43,353	75,259	37,612
OFEDI (Undesirable output)	6.83	6.53	6.99

Source: Sabiha (2016).

undesirable output) is computed to be 6.83. By comparison, farms of the Pabna region produce the lowest OFEDI of 6.53 and realise the highest level of output value (Table 2). The highest OFEDI occurs in Natore (6.99). Soil erosion, crop disease and the associated health impacts (HIs), reduction of fish catch and intensive monoculture practices (expressed by the crop concentration index) are some of the major environmental impacts and therefore increase the undesirable output of this region (Table 3). In Rajshahi, the reduction in the water holding capacity of the soil was ranked as the top impact, followed by crop concentration index, crop disease and pest attack problems. Along with a high crop concentration index, Pabna farms generated a greater amount of HIs from farm chemicals and experienced difficulties in managing the soil compaction problem (SCM), which affected the OFEDI of this region.

4.2 Eco-efficiency results

Table 4 presents the ECE_{D0} and ECE_{D+} scores for HYV rice farms across the study regions. The overall mean ECE_{D0} of HYV rice farms is 69 per cent, which implies that 31 per cent inefficiency in HYV rice production still remains. These results are similar to those reported in other studies on Bangladesh HYV rice agriculture (e.g. Salim and Hossain 2006; Rahman 2011). Rahman (2011) noted that the mean level of technical efficiency of self-

Table 3 Ranks of mean environmental impact indicator scores by study regions†

Impact variables	Rajshahi	Pabna	Natore	All region
CCI (crop concentration index)	0.80 (2)	0.90 (1)	0.69 (5)	0.80 (1)
CDP (crop diseases problem)	0.80 (3)	0.69 (5)	0.77 (3)	0.76 (2)
RFC (fish catch reduction problem)	0.75 (5)	0.70 (4)	0.73 (4)	0.72 (3)
SCM (soil compaction)	0.67 (6)	0.72 (3)	0.58 (6)	0.66 (4)
SER (soil erosion)	0.15 (14)	0.67 (6)	0.90 (1)	0.56 (5)
HI (health impact)	0.19 (13)	0.73 (2)	0.80 (2)	0.56 (6)
PAP (pest attack problem)	0.75 (4)	0.39 (7)	0.42 (7)	0.53 (7)
SWH (soil water holding capacity problem)	0.84 (1)	0.19 (12)	0.09 (17)	0.39 (8)
SFP (soil fertility problem)	0.49 (7)	0.34 (9)	0.29 (9)	0.38 (9)
SSL (soil salinity)	0.20 (11)	0.36 (8)	0.35 (8)	0.30 (10)
SWpH (surface water pH)	0.24 (10)	0.22 (11)	0.26 (12)	0.24 (11)
GWpH (ground water pH)	0.20 (12)	0.27 (10)	0.26 (13)	0.24 (12)
SSF (soil stress factor)	0.25 (9)	0.17 (13)	0.28 (11)	0.23 (13)
NRF (nitrogen risk factor)	0.31 (8)	0.08 (17)	0.23 (14)	0.21 (14)
WLG (waterlogging problem)	0.10 (17)	0.10 (15)	0.29 (10)	0.16 (15)
WDP (water depletion)	0.14 (15)	0.12 (14)	0.21 (15)	0.15 (16)
SpH (soil pH)	0.13 (16)	0.09 (16)	0.17 (16)	0.14 (17)

Notes: Mean values close to '1' imply highest impact (environmental problem). †Rank orders are presented in the parenthesis. Source: Field survey (2013).

selected modern rice farmers is 82 per cent, whereas Salim and Hossain (2006) observed a value of 64 per cent. Both studies noted a substantial scope for improving technical efficiency with the reallocation of available resources and existing technologies. This study successfully addresses that scope of improvement by measuring the environmentally adjusted productive efficiency (or eco-efficiency). The results show that the overall mean ECE_{D+} score is 89 per cent, which implies that an average improvement of 20 per cent in production efficiencies could be realised by minimising on-farm environmental damage (or undesirable output) caused by HYV rice cultivation, which is substantial. Because Bangladesh is a resource-constrained developing country, improving the production efficiency of HYV rice agriculture by an average of 20 per cent by reducing on-farm environmental damage could exert a substantial impact on the farming communities of the country. Nevertheless, the HYV rice agriculture in Bangladesh is considerably eco-inefficient because 11 per cent of inefficiency still exists even after minimising farm-level environmental impacts or reducing undesirable outputs. Picazo-Tadeo *et al.* (2011) also noted that eco-efficiency is closely related to technical efficiency in production and that the farmers are quite eco-inefficient with respect to certain environmental pressures created by farming activities. Table 4 clearly shows that in regions where the on-farm environmental impact is lower, the desirable output is higher and environmental damage-induced loss of production efficiency of the farm is lower. For instance, on average, farms of the Pabna region realised smaller losses of production efficiency (12 per cent, where the OFEDI is 6.53) than those of the Rajshahi (22 per cent, where the OFEDI is 6.83) and Natore (25 per cent, where the OFEDI is 6.99) regions. This discrepancy might be due to the fact that

Table 4 Eco-efficiency scores

	Rajshahi		Pabna		Natore		All region	
	ECE_{D0}	ECE_{D+}	ECE_{D0}	ECE_{D+}	ECE_{D0}	ECE_{D+}	ECE_{D0}	ECE_{D+}
Mean	0.66	0.88	0.81	0.93	0.61	0.86	0.69	0.89
SD	0.20	0.11	0.11	0.06	0.18	0.12	0.18	0.11
Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Min	0.05	0.59	0.56	0.796	0.16	0.55	0.05	0.55
Loss in productive efficiency (mean ECE_{D+} − mean ECE_{D0})	0.22		0.12		0.25		0.20	
Number of farms	113		101		103		317	
Efficiency range	Percentage of the sample farms							
0–0.30	6.19	0	0	0	0.97	0	2.52	0
0.31–0.50	23.89	0	0	0	28.15	0	17.03	0
0.51–0.70	35.39	8.85	19.80	0	40.77	13.59	32.17	7.57
0.71–0.90	28.32	45.13	57.42	41.58	20.38	43.69	35.01	43.53
0.91–1.00	7.96	46.02	22.77	58.42	9.70	42.72	13.24	48.89

Region-wise ANOVA of environmental impact-induced loss in productive efficiency

Source of variation	SS	df	MS	*F*	*P*-value	Critical value of *F*
Between groups	1.15	2	0.57	22.72	0.000	3.024
Within groups	7.94	314	0.03			
Total	9.08	316				

Source: authors' calculation.

farmers of the Pabna region applied farm chemicals to a lower extent and extracted smaller amounts of irrigation water and other inputs of production than farmers of the Rajshahi and Natore regions (Table 2). These results imply that an increased level of eco-efficiency that minimises on-farm environmental impacts would help enhance rice production (Picazo-Tadeo *et al*. 2011). Significant variations in losses of on-farm production efficiency across regions due to the production of undesirable outputs are also indicated by ANOVA statistics (Table 4). Differences in using intensive agricultural technologies among farms and topographical features might cause such variations in production inefficiency.

4.3 Determinants of expected eco-efficiency

Table 5 presents the parameter estimates of the interval regression model used to identify the determinants of expected level of eco-efficiency for

HYV rice farms in Bangladesh. Results of the LR (Likelihood Ratio) test confirm that the explanatory variables, as a group, contribute significantly towards explaining the variation in expected eco-efficiency. Results revealed that extension services and land ownership are the most significant determinants, similar to the finding of Picazo-Tadeo *et al.* (2011) that receiving agricultural extension services improves eco-efficiency. Berre *et al.* (2015) noted that land ownership appeared to be positively related to eco-efficiency, while Alam *et al.* (2011) also noted that owner operators are more technically efficient than tenants. This study shows that farmers who cultivate on owned land and access extension services frequently are more likely to follow environmentally friendly land management practices and exert substantial control over generating adverse environmental impacts. However the proportion of farmers' income from HYV rice agriculture is positively related to the expected level of eco-efficiency.

In exploring determinants of farm-level eco-efficiency, Picazo-Tadeo *et al.* (2011) noted that conventional socio-economic variables can barely explain variations in eco-efficiency. This study also found that some of the most commonly used socio-economic determinants, for example farmers' education, age and experience, showed the desired positive sign but were statistically insignificant. Following Estoque and Murayama (2014), we found that farmers' socio-environmental living index was one of the important determining factors. The farmers' socio-environmental index (SELI) was found to be statistically significant and positively related to the expected eco-efficiency, implying that environmentally conscious farmers who have an environmentally friendly lifestyle and release less household pollution are likely to have higher eco-efficiency in farming.

Table 5 Determinants of the expected eco-efficiency in Bangladesh high-yielding variety rice farms

Explanatory variables	Coefficients	Dependent variable 1 Dependent variable 2 SE	ECE_{D0} ECE_{D+} *P* values
Constant	0.5344***	0.741	0.000
AGE	0.00064	0.006	0.313
EDU	0.00918	0.001	0.606
EARN	0.01847	0.057	0.784
AGIN	0.07063***	0.024	0.004
EXP	0.05887	0.036	0.110
LNDW	0.03467**	0.188	0.065
EXTN	0.05651***	0.014	0.000
SELI	0.11123**	0.057	0.054
Log-likelihood	−360.86		
LR $chi^2(8_{df})$	40.28***		0.000
Number of observations: 317 (uncensored observations: 23; interval observations: 294)			

Source: authors' calculation. *** and ** denote 1% and 5% level of significance.

5 Conclusions and policy implications

The principal aim of this study was to measure the eco-efficiency of HYV rice agriculture to evaluate the prospect of agricultural sustainability based on a survey of 317 HYV rice farmers from three regions of north-western Bangladesh. To this end, an OFEDI was computed by incorporating three groups of environmental indicators (i.e. farming practice-related, farming system-related and farmer's perception-related indicators), which were then added as an undesirable output in conventional production efficiency modelling. Then, the environmentally adjusted production efficiency (or eco-efficiency, ECE_{D+}) was evaluated for the set of surveyed farm units, and conventional production efficiency scores were computed without adjusting for environmental damage (i.e. by assigning zero values for OFEDI variable, ECE_{D0}). Results revealed that, given the available resources and existing technology, 20 per cent of the production efficiency of HYV rice farming is lost by generating on-farm environmental damage or producing undesirable outputs. In addition, the environmental impact-induced loss of production efficiency was found to be higher in regions where environmental damage is higher, which is consistent with the assertion of Poit-Lepetit *et al.* (1997), who noted that in the presence of an external impact (e.g. environmental damage) generated by the use of a particular production technology, technical efficiency could decrease persistently and initiate increasing external impacts.

Results further revealed that improvements in the expected level of eco-efficiency, that is minimising on-farm environmental damage, are significantly related to farmers' socio-economic and socio-environmental attributes. These attributes include access to extension services, ownership of agricultural land, income share from HYV rice agriculture and socio-environmental living standard.

The main policy implication that can be drawn from this study is that there is substantial scope for increasing production efficiency in HYV rice farming by minimising on-farm environmental damage or the production of undesirable outputs. These goals can be achieved by making investments in improving farmers' socio-environmental living standard, extension services and land reform measures aimed at improving land ownership among farmers.

The approach used in this study can also be replicated, with minor adjustments, for evaluating other agricultural activities. The OFEDI used in this study to measure eco-efficiency represents a comprehensive method for incorporating a wide range of dimensions into a single index that provides an indication of potential threats in realising agriculture sustainability. In addition, comparative analyses of the eco-efficiency scores (i.e. ECE_{D0} and ECE_{D+}) would assist agroecological researchers and policymakers to adopt policies by providing them information for targeting factors that contribute directly to efficiency improvements while promoting the goal of achieving environmental sustainability in agriculture.

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Appendix

The raw data value of the SSF is calculated as follows:

$$\mathrm{SSF}_i = [\sum_{t=1}^{3} t] \times r,$$

where, t, weighted value of the tilling machine; (t = Bullock (value 1); power tiller (value 2); tractor (value 3); r = number of tilling for land preparation; (r = 2…6). Therefore, the theoretical maximum value of the soil stress factor due to tilling practice is 36 (sum of all weights (1 + 2 + 3 = 6) multiplied by the highest number of tilling found in the survey (i.e. 6)), whereas the minimum value of SSF is 2 (minimum weight for tilling method used (i.e. 1) multiplied by the minimum number of tilling observed in the survey (i.e. 2)).

Socio-environmental living index (SELI)

SELI is computed by the weighted sum of farmers' socio-environmental living attributes expressed below in Table A1. SELI values close to 1 imply that farmers have better environmentally friendly living standards, whereas values close to 0 indicate otherwise.

Table A1 Environmentally friendly activity weights (Ew)

Attributes (*r*)	(1) Least	(2) Good	(3) Better	(4) Best
1. House Category	Clay	Straw	Half-concrete	Full-concrete
2. Sanitation	Open place	Temporary latrine	Sanitary latrine (without water seal)	Sanitary latrine (with water seal)
3. Access to health facility	Village doctor	Health centre	Clinic	Hospital
4. Drinking water source	Pond/river	Well	Supply	Deep tube well
5. Household energy source	Timber/straw/cow dung/dried leafs/ Kerosene	Electricity	Biogas/natural gas	Solar power
6. Waste disposal	No specific place to dispose	Burnt	Buried	Specific place/ waste bin

$$\mathrm{SELI}_i = \sum_{r=1}^{6} \mathrm{Ew}_r/24. \tag{A1}$$