Do organic fertilizer impact on yield and efficiency of rice farms? Empirical evidence from Bangladesh

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ABSTRACT

Organic fertilizer is one of the critical elements of organic and sustainable agricultural development. This study analyzes the economic impact of organic fertilizer on rice farms' yield and technical efficiency (TE) in Bangladesh. The Stochastic Production Frontier (SPF) approach has been employed by using a sample of 2652 rice plots covering seven broad agro-ecological zones of Bangladesh. It also addresses self-selection into the organic fertilizer choice using propensity score matching (PSM) that corrects observed selection bias that potentially influences both decisions to choose and technical efficiency. After PSM, organic fertilizer users produce higher yield by using 12.1%, 9.40%, and 42.1% less labor, other inputs, and farm capital for rice production. The average treatment effect on the treated (ATETs) in different matching is positively significant. Organic fertilizer users are significantly more efficient than non-user, suggesting organic fertilizer substantially contributes to enhancing the technical efficiency of rice in Bangladesh. Moreover, the average treatment effect on the treated (ATETs) in different matching is positively significant and confirms the positive impact of organic fertilizer on rice farming. Government and non-government organizations should encourage farmers to use organic fertilizer for better production through soil health development and reduce the pressure of chemical fertilizer import and use.

1. Introduction

The global population is increasing rapidly and is expected to be 8.6, 9.8, and 11.2 billion by 2030, 2050, and 2100 respectively (Tripathi et al., 2019). Increasing safe agricultural production is the only way to feed this huge number of people. However, scientists proposed many practices to increase agricultural production, like the use of inorganic fertilizers, pesticides, hormones, and herbicides (Cen et al., 2020). But all these practices can cause a serious problem in human health. Organic agriculture is a potential alternative production system where organic fertilizers can ensure safe agricultural production without harming people, soil, and the environment due to its organic contents (Ferdous et al., 2021). However, a major portion of the global population is dependent on agriculture, and it is very common in developing countries like Bangladesh. Hence, increasing safe agricultural production can help to ensure food safety and security. Though a few studies have already been conducted in different countries on organic fertilizer's application related factors on vegetable production (Babasola et al., 2018), maize production (Ahmed and Melesse, 2018), sorghum production (Abd El-Mageed et al., 2018), but a very little focus on rice production. As a major crop in the world, understanding organic fertilizer's impact on rice farms is necessary to increase global rice production.

Bangladesh's economy is predominantly dependent on agriculture. It remains the largest employment sector in the country, where about 47.5% of the population directly and around 70% of people's livelihood indirectly depend on agriculture. The contribution of agriculture to the gross domestic product (GDP) in Bangladesh is nearly 17% and employs more than 47% of the total labor force (BER, 2015). Rice is the most important and main crop in Bangladesh, occupies almost 76% of the total cropped area, and its share of total food grain production is over 92% (BBS, 2015). Agricultural and total GDP has increased by 5.6 times and 20.8 times since independence, while gross national income (GNI) has improved by 6.2 times (GOB, 2015). Every year, about 1% of cultivable land has shifted to the non-agricultural purpose (Planning Commission, 2012), which is alarming for Bangladesh’s food security (Rahman, 2003). The increasing demand for rice with the growing population in Bangladesh has created pressure on producers and the government to confirm the availability of staple food on every consumer (Baumgartner et al., 2017). Productivity growth is a crucial component of economic growth in Bangladesh, and rice productivity is the most critical driver to
increase per capita income in the rural economy of Bangladesh (Nasrin et al., 2018). It is necessary to improve productivity by improving high yielding variety (HYV) and cost-saving technology to ensure staple food availability.

As a significant input for rice production, fertilizers get high priority from Bangladesh’s government and provides subsidy on chemical fertilizer every year to enhance rice production. Organic fertilizer is one of the critical elements of organic and sustainable agricultural development. Due to the increasing demand for fertilizer, Bangladesh’s government spends enormous funds importing various chemical fertilizers every year. On the other hand, most Bangladeshi rice farmers do not follow the recommendation guide of fertilizer due to a lack of awareness about soil fertility and appropriate fertilizer use knowledge. As a result, long-term use of chemical fertilizer can negatively affect crop productivity and soil health (Howarth et al., 2014).

Moreover, the rising production cost and shortage of chemical fertilizer, an alternative to chemical fertilizer is needed. Organic fertilizer (green compost) technology can be one of the best alternatives to improve soil health, fertility, and productivity and meet the nutritional requirement of rice. It can reduce the pressure of chemical fertilizer import as well as government expenses (Baumgartner et al., 2017). Organic fertilizer protects soil health in good condition by enhancing the supply of nitrogen and promoting microorganisms’ growth. It also develops soil structure and increases soil fertility and water holding capacity by adding nitrogen that is very useful for crop production (Howarth, 2001). Application of organic fertilizer for the supplement of chemical fertilizers and restores soil fertility can reduce chemical fertilizers, pesticides, and labor that help to practice organic farming with more output and earn more revenue (Marchand and Guo, 2014).

Although the researchers and farmers of Bangladesh know that the use of organic fertilizer could be reduced the requirement of chemical fertilizer through soil nutrient development. However, no studies have evaluated how much of these organic fertilizers influence on yield and efficiency of rice production. Previous researches have been done on mulching and composting (Termorshuizen et al., 2004; Jusoh et al., 2013), fertilizer management (Srivastava et al., 2016), green wastage usage (Gong et al., 2018; Eldridge et al., 2018), rice yield (Rahman, 2003; Thakuria et al., 2009; Bäckman et al., 2011; Barison and Uphoff, 2011; Kabir et al., 2016). However, organic fertilizer’s impact on rice production and technical efficiency is still a gap in research. Although, many studies have estimated stochastic frontier production for farms to analyze technical efficiency and contributions of different inputs (Battese and Coelli, 1995; Greene, 2005; Bäckman et al., 2011; Kabir et al., 2016; Gautam and Ahmed, 2019). However, almost no one focuses on applying organic fertilizer with correction of sample selection for rice production. Therefore, this paper intends to analyze the impact of organic fertilizer on yield and efficiency of rice farms in Bangladesh. One of this paper’s main contributions is to apply propensity score matching (PSM) to make a counterfactual group that correct selection biases which come from observable factors and deliver a detailed analysis of the rice farms’ technical efficiency in Bangladesh by estimating the stochastic production frontier (SPF) separately.

2. Methodology

2.1. Econometric framework and estimation strategies

Organic fertilizer is likely endogenous to selection choice and hence, unobserved and uncaptured household characteristics such as farm household head ability to influence organic fertilizer choice. This study’s primary focus is to address how the application of organic fertilizer affects the productivity and efficiency of rice farms in Bangladesh. This self-selection into organic fertilizer involvement potential source of endogeneity, and it could be estimated biased results. To examine the impact of organic fertilizer on yield and efficiency, this study generates a group of comparable control farmers, i.e., who does not use organic fertilizer, by using PSM to control biases from observable factors and self-selection in the SPF model.

2.2. Stochastic production frontier model

Technical efficiency (TE) denotes the capability to provide the highest achievable output from a given same set of inputs (Farrell, 1957; Ahmed and Melesse, 2018), and any shortage from this maximum output is measured as technical inefficiency (Coelli et al., 1998). Following Mayen et al. (2010), this study adopts a parametric approach, precisely SPF structure to estimate production frontier and technical efficiency, which is expressed as follows:

\[
\ln Y_i = X_i \beta + v_i - u_i
\]

Where, \( Y_i \) is the observed yield of rice of the \( i^{th} \) plot \((i = 1, 2, 3, ..., N)\), \( X_i \) is the vector of inputs variable used by the \( i^{th} \) plot, \( \beta \) is a vector of the parameter to be projected and \( v_i \) is the statistical noises term that assumed to be identically and independently distributed idd \( \sim N(0, \sigma^2_v) \). The term \( u_i \sim N(0, \sigma^2_u) \) is a non-negative half-normal stochastic term accounting for technical inefficiency in production. The maximum likelihood approach is used to calculate unknown parameters by the SPF and inefficiency effect function simultaneously. The stochastic term \( u_i \) and \( v_i \) are assumed to be uncorrelated and expressed in terms of \( \sigma^2_u \) and \( \sigma^2_v \) respectively. The proportion of the variance has been explained by inefficiency, \( \lambda_i = \sigma^2_u / \sigma^2_v \) (Battese and Coelli, 1995). The density function for \( \epsilon_i \) is correlated with the disturbance term \( \sigma^2_v \).

\[
f_i(\epsilon) = (2 / \pi \sigma^2_v \epsilon (1 - \Phi(\lambda \epsilon)) \Phi(\lambda \epsilon)), \text{for} \quad -\infty < \epsilon_i < + \infty
\]

Where, \( \phi \) is the standard normal density and \( \Phi \) is the standard normal cumulative distribution function. The technical efficiency is the ratio of observed output to the corresponding stochastic frontier output is defined as:

\[
TE_i = \frac{Y_i}{\exp(X_i \beta)} = \frac{\exp(X_i \beta + v_i - u_i)}{\exp(X_i \beta + v_i)} = \exp(-u_i)
\]

2.3. Self-selection into organic fertilizer choice

The frontier production can vary between users and non-user of organic fertilizer because of the constraints on the production practice executed by applying organic fertilizer. The parameter of the production function \( \beta \) is different for organic fertilizer users and non-user. It also includes the indicator variable for choice organic fertilizer that relates to the input vector \( X_i \). Organic fertilizer choice maybe formed a propensity \( P_i^* \), the model which depends on observable characteristics, \( w_i \) are expressed as follows:

\[
P_i^* = w_i \alpha + \delta_i
\]

The term \( \alpha \) denotes unknown parameters to be calculated and \( \delta_i \) denote a random error. If the factors of choice model, \( w_i \), also influence rice production but excluded from Eq. (1), and then the choice indicator variable in (1) is correlated with the disturbance term \( \epsilon_i \). In this case, the estimators of \( \beta \) are biased due to the endogeneity of the organic fertilizer choice.

Many previous studies have used SFPs to compare the groups’ technical efficiency, but they fail to overcome selectivity bias. For example, following Heckman (1979) methodology, many researchers tried to overcome sample selection bias by adding an inverse Mill’s ratio in the frontier function (Rahman, 2011; Solis et al., 2007). This study adopts the PSM approach to overcome self-selection to examine the impact of organic fertilizer application on rice farms’ yield and technical efficiency.
The effect of organic fertilizer on productivity is explained as $E(Q_i - Q_0 | Z, G = 1) = E(Q_i | Z, G = 1) - E(Q_0 | Z, G = 1)$, where $Q_i$ denotes yield of rice of organic fertilizer non-user ($G = 0$), and $Q_i$ represents yield of rice who use organic fertilizer ($G = 1$) and $Z$ is a vector of variables comprising of any $X$ variables from (1) and any $w$ variables from (4). The mean $E(Q_i | Z, G = 1)$ may be determined from data of organic fertilizer application but its requisite to be made to detect the counterfactual mean $E(Q_0 | Z, G = 1)$. By using the outcome of self-selected non-user $E(Q_0 | Z, G = 0)$ to estimated $E(Q_0 | Z, G = 1)$ selection bias result, which making such an estimation which defined as $E(Z) = E(Q_i | Z, G = 1) - E(Q_0 | Z, G = 0)$. The PSM technique find a substitute for $E(Q_0 | Z, G = 1)$ on the basis of statistical independence of $(Q_0, Q_1)$, and $G$ conditional on $Z$, where PSM reduces the variability of having a match on $Z$. If this is assumptions hold, then $E(Q_i | P(Z), G = 1) = E(Q_i | P(Z), G = 0) = (Q_0 | P(Z))$, agreeing an unbiased estimate of $E(Q_i - Q_0 | Z, G = 1)$.

Furthermore, according to Villano et al. (2015), we test the balancing property to ensure that the samples within the common support area have the same distribution of observable characteristics, regardless of whether the farmer has used organic fertilizer or not. Thus we use average treatment effect on treated (ATT$E$) to assess the effect of organic fertilizer use because ATT$E$ is the parameter of interest in PSM. ATT$E$ is computed by matching organic fertilizer users and non-user closest in terms of their propensity scores. In this study, the ATT$E$ is the average impact of treatment on those who use and assume no selection biases. The ATT$E$ is calculated as follows:

$$\text{ATT} = E(Q_i | G = 1) - E(Q_i | G = 0)$$

Where $Q_i$ and $Q_0$ are the yield of rice for organic fertilizer users and non-users, respectively, and $G$ is the dummy variable equal to 1 if the farmer uses organic fertilizer, and otherwise zero.

This study follows three steps to estimates the impact of organic fertilizer. First, the PSM technique is employed to choose organic users first. The PSM technique is commonly used to make such a group. Several matching criteria can be used in implementing PSM. Here we employ the single nearest-neighbor matching by utilizing the “1-to-1” nearest neighbor without replacement” criterion where every organic user is matched with a non-user imposing the common support condition. After estimating the probit model, this study predicts the propensity scores based on the common support region, leading to the total matched observation of 2686, of which 1343 for the organic user and 1343 for non-user. Table 1 represents a summary and comparisons of the mean value along with the t-test. Once the samples of organic fertilizer users and non-user are matched, we estimate the SPF model separately. In this regard, the model to choice of the $i^{th}$ farm household to the application of organic fertilizer and estimated the following specification of (4) to get propensity scores are expressed as:

$$pr(P_i = 1) = \mathbf{w} \alpha + \epsilon_i$$

The term, $\mathbf{w}$ denotes a farm and farmer characteristics that explain the decision to the choice of organic fertilizer of farmers and $\mathbf{w}$ represent parameters to be estimated, and $\epsilon$ is the disturbance term $N(0, \sigma^2)$. Then, the following production structure of translog stochastic production frontier in Bangladeshi rice farmer using single output, multiple inputs, and the particular form of the SPF for the $i^{th}$ farm plot is expressed as follows:

$$\ln(Q_i) = \beta_{0i} + \sum\limits_{j=1}^{5} \beta_{j} \ln(X_{ji}) + 0.5 \sum\limits_{j=1}^{5} \sum\limits_{k=1}^{5} \beta_{jk} (\ln(X_{ji})) (\ln(X_{ki})) + yD + \nu_i - u_i$$

and,

$$u_i = \delta_{0i} + \sum\limits_{d=1}^{12} Z_{i} \delta_{d} + \omega_i$$

Where, $X_{ji} = A_i, X_{1i} - L_i, X_{2i} = F_i, X_{3i} = O_i$, and $X_{4i} = K_i$. Variables $Q_i, A_i, L_i, F_i, O_i$, and $K_i$ respectively denote rice output, land, labor, cost of fertilizer, cost of other inputs (including pesticide, seed, rental tools and machinery, and irrigation (in cash)), and the current value of farm capital. Variable $D_i$ includes different dummy variables such as rice season, soil type, rice variety, and agro-ecological zone dummy. The variables $Z_i$ represents the household’s farm size, the dummy for the gender of the decision-maker, household head’s age, household head’s years of education which may influence productivity and efficiency through better management, respectively. The term $Z_i$ also denotes the land fragmentations of the household, participation in wage work, access to extension service, family size, and plot distance from home measured in the meter, which may influence production through easy access for management, flood depth that influences rice production through affecting by flood especially in the rainy season, market distance and access to credit respectively. The term $\delta_{0i}$ is the unknown parameter to be calculated and $\omega_i$ denote a truncation of half-normal distribution N(0, $\sigma^2$). Unknown parameter with SPF and inefficiency effect model is estimated simultaneously by using maximum likelihood method.

2.5. Ethical approval

Our study solely focuses on the secondary data obtained from Bangladesh Climate Change Adaptation Survey 2010–2011. All ethical standards have been maintained during the research process.

3. Data and descriptive statistics

This study uses data from the first round of the Bangladesh Climate Change Adaptation Survey which was conducted in 2010–2011 under the supervision of researchers from the International Food Policy Research Institute (IFPRI). This survey comprised 800 households, including information on demographic features, land tenure, crop and livestock production, agricultural input, extension service, etc. The household survey covered 40 unions (local administrative units), selected to represent the 7 broad agro-ecological zones (AEZs) such as Barind tract (AEZ-BT), Bill and haor basin (AEZ-BBBH), Flood plain (AEZ-FP), Himalayan Plain (AEZ-HPP), Modhupur tract (AEZ-MT), Northeastern hill (AEZ-NEH), Tidal flood plain (AEZ-TFP), and (Thomas et al., 2013) explained in detail about agro-ecological zones. The original data at individual and household levels were reported that 800 households had 4987 crop agriculture plots during the twelve months, of which 757 households having 3438 rice plots in different seasons. After dropping plots for zero output, this study used 3253 observations of which 1343 for organic fertilizer (green compost) users and 1910 for non-user for relevant variables. We construct plot-level data, which provides information on inputs and outputs for each crop planted on all plots. The output is defined as the quantity harvested on a plot (in kilogram). The land is an area planted (in hectare), and rice yield is obtained by dividing output by land (kg/ha). Total farm labor is defined as the sum of family
and hired person-day aggregated over sex. Fertilizer is the sum of costs for eight types of fertilizers (urea, triple superphosphate/single superphosphate, di-ammonium phosphate, muriate of potash, zinc, ammonia, gypsum, NPKS, and manure) evaluated at the corresponding fertilizer prices at the household level. Other costs are the sum of costs for pesticides, ploughing cost, irrigation cost, and seed cost. Finally, the value of farm assets is the total current value of productive farm assets reported at the household level.

The summary statistics of the variables of the two groups (organic fertilizer user and non-user) for matched and unmatched samples are presented in Table 1. The Table represents the variable’s mean differences and t-test between the groups for before and after matching. This study found the number of significant variables reduces after PSM, which indicates PSM reduces the variable’s variance. The yield of rice by organic fertilizer in their plots is 6.3% higher than non-user due to soil health improvement. However, this difference stands at 16.67% after PSM. The summary statistics also reveal that before PSM, the farmers who use organic fertilizer require 12.1%, 9.40%, and 42.1% less labor, other inputs, and farm capital for rice production, respectively. Clay loam soil is the major soil type for rice production, and boro and aman is the dominant season in Bangladesh, where most of the plots are planted in a high yielding variety (HYV) in both groups. However, organic fertilizer users planted 3% higher plots for the hybrid variety than non-user, which may help to increase the yield difference between the groups. Less distance of plot is more prefer for using organic fertilizer due to less time required for management. About 47% of non-user farmers have access to extension service, although they have a lower yield than users, indicating they did not care about extension service. This study also observes that credit access is significantly higher in the non-user group than the user, indicating non-users group invests more in other purposes than farming. Older and higher educated farmers use organic fertilizer, which reveals that higher education with age is more aware and better experience about organic fertilizer. Larger family members have more opportunities to engage in on-farm practice due to available family labor, and it shows that family size is significantly higher in users than non-users. The agro-ecological dummy indicates that maximum samples are obtained from flood plain zone (AEZ-FP).

| Table 1. Summary statistics of relevant variables. |
|-----------------------------------------------|
| Unmatched | Organic user | Mean | SD | Non-user | Mean | SD | Matched | Non-user | Mean | SD |
| Output (kg/ha) | 4666.5 | 4691.1 | 4388.7 | 4332.8* | 4000.3 | 4000.3 |
| Land (ha) | 0.144 | 0.121 | 0.172 | 0.497** | 0.144 | 0.121 |
| Labor (md/ha) | 123.02 | 67.11 | 140.38 | 133.94*** | 153.16 | 78.27*** |
| Fertilizer cost (Tk.000/ha) | 6.36 | 11.09 | 6.49 | 6.69 | 5.22 | 3.89*** |
| Other cost (Tk.000/ha) | 13.88 | 11.44 | 15.32 | 13.30*** | 14.25 | 10.60 |
| Farm capital (Tk.000/ha) | 34.19 | 145.89 | 59.00 | 340.94*** | 64.35 | 266.5*** |
| Soil type: clay | 0.014 | 0.118 | 0.020 | 0.140 | 0.017 | 0.130 |
| Loam | 0.264 | 0.441 | 0.277 | 0.448 | 0.200 | 0.400*** |
| Sandy loam | 0.448 | 0.497 | 0.470 | 0.499 | 0.445 | 0.497 |
| Sandy | 0.202 | 0.401 | 0.194 | 0.396 | 0.228 | 0.420** |
| Season: Aus | 0.182 | 0.386 | 0.134 | 0.341*** | 0.093 | 0.291*** |
| Aman | 0.386 | 0.487 | 0.425 | 0.494** | 0.448 | 0.497*** |
| Boro | 0.363 | 0.481 | 0.355 | 0.479 | 0.340 | 0.474 |
| Variety: local | 0.146 | 0.353 | 0.119 | 0.324** | 0.230 | 0.421*** |
| HYV | 0.765 | 0.424 | 0.824 | 0.381*** | 0.716 | 0.451*** |
| Hybrid | 0.089 | 0.284 | 0.058 | 0.233*** | 0.054 | 0.227*** |
| Extension service | 0.265 | 0.442 | 0.469 | 0.499*** | 0.265 | 0.442 |
| Access loan | 0.436 | 0.496 | 0.516 | 0.500*** | 0.436 | 0.496 |
| Plot distance | 406.1 | 734.5 | 532.8 | 1360.6*** | 406.1 | 734.5 |
| Flood depth | 1.293 | 2.837 | 1.494 | 2.367*** | 1.29 | 2.83 |
| Sex (male) | 0.961 | 0.195 | 0.960 | 0.196 | 0.920 | 0.272*** |
| Age | 47.92 | 13.82 | 46.07 | 13.94*** | 46.78 | 14.76*** |
| Education | 3.874 | 4.322 | 3.779 | 4.489 | 3.771 | 4.242 |
| Land piece | 6.337 | 3.583 | 7.339 | 4.862*** | 6.337 | 3.583 |
| Family size | 5.509 | 3.245 | 5.174 | 2.902*** | 5.509 | 2.425 |
| Wage work | 0.048 | 0.215 | 0.072 | 0.258 | 0.048 | 0.215 |
| AEZ-BT | 0.150 | 0.358 | 0.175 | 0.380* | 0.150 | 0.358 |
| AEZ-BHB | 0.045 | 0.208 | 0.103 | 0.304*** | 0.045 | 0.208 |
| AEZ-TP | 0.225 | 0.418 | 0.262 | 0.440*** | 0.225 | 0.418 |
| AEZ-MT | 0.144 | 0.351 | 0.126 | 0.332 | 0.144 | 0.351 |
| AEZ-TP | 0.077 | 0.267 | 0.109 | 0.312*** | 0.077 | 0.267 |
| AEZ-NEH | 0.158 | 0.365 | 0.125 | 0.331*** | 0.158 | 0.365 |
| AEZ-TFP | 0.200 | 0.400 | 0.101 | 0.301*** | 0.200 | 0.400 |

Observations: 1343 1910 1343

Note: “*, **, ***” denote significance at 10%, 5%, 1% level.
4. Results and discussion

4.1. PSM for finding the proper counterfactual group of organic fertilizer users

We first check whether there is reason to be concerned with self-selection into the choice of green compost by following Mayen et al. (2010). To do so, we conduct a Durbin-Wu-Hausman (DWH) test for endogeneity of the green compost dummy variable in Eq. (7). The DWH test result shows that the chi-squared statistics from a Wald test is 39.57 with 1 degree of freedom (p-value = 0.00001). We reject the null hypothesis that the organic fertilizer dummy is exogenous at the 1% level.

To find a counterfactual group for the green compost user, we use the probit estimates to generate a propensity score (PS) for each observation based on the common support region are predicted. We then match each organic fertilizer user with the non-users with the closest propensity score. Figure 1 revealed the density estimation of the propensity score distribution for organic fertilizer users and non-user, besides with and without common support area. Moreover, in evaluating the reliability of the above-reported estimates, we carried out several tests to check whether the balancing requirements of PSM are satisfied in our data. The balancing test based on kernel matching shows that organic fertilizer users and non-users have statistically similar characteristics after matching in contrast to the unmatched sample. We found the standardized differences (% bias) for the mean values of almost all covariates between users and non-users are 7.3%. This result assures that the balancing requirement is adequately satisfied. Moreover, the distributions of the estimated propensity scores for organic fertilizer users and non-users before and after matching are presented in Figure 2 for visual inspection. As expected, the two groups have a significant overlap in their propensity score distributions.

![Figure 1. Distribution of propensity score for organic fertilizer users and non-users.](image1)

![Figure 2. Test of matching quality before and after PSM.](image2)
The estimation of the probit regression model for the choice of organic fertilizer of rice farms in Bangladesh has been presented in Table 2. Marginal effects also estimate to allow better interpretation of the results (Abdul-Rahaman and Abdulai, 2018). The result reveals that education of household heads have a positive and significant effect on the choice of organic fertilizer that indicates educated farmers are more prone to the use of organic fertilizer. A larger family size implies that the rice farmers have sufficient labor for the farm activities as well as the application of organic fertilizers than the small family size. This outcome is consistent with Chianu and Tsujii (2005) and Babasola et al. (2018).

Farm size has a negatively significant effect and reduces the 12.7% probability of applying organic fertilizer, which indicates that small farms are more prone to use organic fertilizer. This might also mean a large farm requirement for more investment in organic fertilizer. Loam-type soil negatively associates with the choice of organic fertilizer, indicating the requirement of soil nutrients already exists in this soil type (Islam et al., 2020). The distance to the nearest market has a negatively significant impact on organic choice indicating farm plots are in remote areas which is supported by Hammed et al. (2019). Participation in extension service negatively influences choice organic fertilizer, revealing that farmers are not aware of organic fertilizer or lack available organic fertilizer sources. However, opposite relations were found by Abebe and Debebe (2019). The farmers who have access to sufficient credit facilities are less likely to apply organic fertilizer than those who have no credit-constrained, indicating that farmers may use their credit for food security requirements than farming practice. All significant agro-ecological zones except the Tidal flood plain are less probability to use organic fertilizer than Barind Tract zone.

### 4.2. Hypothesis testing and variance parameters for the SPF model

Before estimating the maximum likelihood, we test several hypotheses to know whether the chosen SPF model is appropriate to explain the impact of organic fertilizer on rice production in Table 3. The first of these is a log-likelihood ratio (LR) test to decide the functional form, and LR test confirmed that the choice of translog production function is more suitable than the Cobb-Douglas production function. Many previous studies about Bangladesh agriculture have used LR test for model selection, including Anik et al. (2017). Secondly, we checked the null hypothesis that is no skewness of OLS residual based on the third-moment test \( M_3T = m_3/\sqrt{m_4^2} \) proposed by Schmidt and Lin (1984). The term \( m_2 \) and \( m_3 \) denote the 2nd and 3rd sample moments of the OLS residuals, respectively. We found the estimated value of the test statistic for the organic users and non-users is negative and confirms the rejection of the null hypothesis and existence of inefficiency effects. Thirdly, the hypothesis \( H_0 : \delta_3 = \delta_4 = \ldots = \delta_{12} = 0 \) indicates that the inefficiency effects in the frontier model are not present, which is rejected, meaning the exogenous variables should be incorporated into the mean output function. The fourth hypothesis, \( H_0 : \delta_3 = \delta_4 = \ldots = \delta_{12} = 0, \) argues that the exogenous variables do not explain variation in technical efficiency, which is also rejected. The rejection here argues that the combined effects of factors involved in the technical inefficiency model are important in explaining the variation in rice production.

### 4.3. Parameter estimates of the SPF model

This study’s main attention is to measure technical efficiency differences between the groups with correcting selection bias. After matching, the next step is to decide if the SPF should be run for the pooled sample or if separate frontiers are required between the groups. Following Ahmed and Melesse (2018), this study conducted an LR test is expressed as follows:

\[
LR = 2 \times (\ln L_{pool} - (\ln L_u + \ln L_n)),
\]

Where, \( \ln L_{pool}, \ln L_u \) and \( \ln L_n \) represent the obtained log-likelihood function values from the pooled model, organic user, and non-user, respectively. This study estimated SPF with pooled sample by including organic fertilizer as a regressor, indicating whether the household applied organic fertilizer or not and estimated SPF for each group separately. Pooled SPF indicated organic fertilizer in both unmatched and unmatched significantly affect on technical efficiency. The LR test rejects the null hypothesis of homogenous technology between the groups at 1% level for the unmatched \( (LR = 164.05, \chi^2 = 54.17, df = 33) \) and matched \( (LR = 447.48, \chi^2 = 54.17, df = 33) \) respectively, which confirm the production frontiers’ parameters vary between the two groups and support the estimation of separate SPF models for each group. The estimated results of the SPF function in before and after PSM are shown in Table 4. For estimating the SPF, the input variables \( (X_1, X_2, \ldots, X_{12}) \) are divided by their respective mean. Therefore, the coefficients of these variables can be described as the output elasticities of the corresponding inputs evaluated by their mean.

We checked the variable organic fertilizer dummy in the pooled model representing positive and significance for both before and after PSM, suggesting that organic fertilizer application is associated with higher rice productivity. The size of the output elasticities is different between users and non-user of organic fertilizer and statistical significance, and relative relations of the output elasticities are very similar.

### Table 2. Estimate result for factors determining organic fertilizer.

|         | Probit coefficient | Marginal effects |
|---------|--------------------|------------------|
|         | Coef. S.E.         | Coef. S.E.       |
| Age     | 0.004 0.002***     | 0.001 0.001***   |
|         | 0.030 0.006***     | 0.010 0.002***   |
| Family size | 0.064 0.011*** | 0.022 0.004***   |
| Farm size | -0.366 0.044***  | -0.127 0.015***  |
| Soil type: Clay | -0.209 0.212 | -0.072 0.073    |
| Loam    | -0.276 0.114***   | -0.096 0.039***  |
| Clay loam | -0.163 0.109     | -0.057 0.038    |
| Sandy loam | -0.098 0.116   | -0.034 0.040    |
| Market distance | -0.059 0.012*** | -0.200 0.04***  |
| Extention service | -0.442 0.053*** | -0.153 0.018*** |
| Access credit | -0.187 0.048*** | -0.065 0.016*** |
| Cattle  | 0.099 0.016***    | 0.034 0.005***   |
| AEZ-BHB | -0.582 0.110***   | -0.201 0.038***  |
| AEZ-FP  | -0.263 0.078***   | -0.091 0.027***  |
| AEZ-HP  | -0.187 0.091***   | -0.065 0.032***  |
| AEZ-MT  | -0.269 0.097***   | -0.093 0.033***  |
| AEZ-NEH | 0.067 0.091       | 0.023 0.031     |
| AEZ-TFP | 0.261 0.088***    | 0.125 0.030***   |
| Constant | -0.037 0.154      |                    |
| L. likelihood | -1.971.44     |                    |
| LR chi^2 (\(\chi^2\)) | 467.41***     |                    |

Note: ‘*’ ‘**’ ‘***’ indicate significance at 10%, 5%, 1% level.

### Table 3. Hypothesis tests for model specification and statistical assumptions.

|                | Organic fertilizer users | Organic fertilizer non-users |
|----------------|--------------------------|-----------------------------|
| Null hypothesis | Test statistics | Decision | Test statistics | Decision |
| \( H_0: \beta_0 = 0 \) | 99.84 | Reject \( H_0 \) | 126.13 | Reject \( H_0 \) |
| Third-moment test (\( M_3T \)) | -5.81 | Reject \( H_0 \) | -2.22 | Reject \( H_0 \) |
| \( H_0: \delta_3 = \delta_4 = \ldots = \delta_{12} = 0 \) | 122.36 | Reject \( H_0 \) | 104.97 | Reject \( H_0 \) |
| \( H_0: \delta_3 = \delta_4 = \ldots = \delta_{12} = 0 \) | 54.77 | Reject \( H_0 \) | 40.41 | Reject \( H_0 \) |

Note: Critical values are taken from Table 1 of Kodde and Palm (1986) using a 1% level of significance.
Return to scale estimated by the sum of the production elasticities of all inputs, and we found that the structure of production is different between the groups. Our result shows that both groups are operating under decreasing return to scale (0.9488 and 0.9436). Although, before PSM, the organic fertilizer non-users were operating increasing return to scale (1.073). The trans-log function (Table 4) produced 0.555 (organic users) and 0.747 (matched non-users) Gamma value respectively that explains the percentage variation in frontier output as a result of the presence of efficiency effects (group-specific variable) and suggests that external factor has an influence on rice production in Bangladesh.

The elasticity of land is 0.845 for organic fertilizer users, where it is 0.635 for non-user, implying that a 1% increase in the cultivated area will increase rice yield by 21% more for organic fertilizer users than non-user may be the effect of improved soil nutrition. The elasticity of labor is insignificant for both groups, implying marginal productivity of labor decreasing and abundance in labor in Bangladesh and confirming that the farmer uses optimum labour. The elasticity of chemical fertilizer is significantly higher for non-user than users, confirming that organic fertilizer users are more close to optimum use of fertilizer. These estimates are consistent with those estimated by other studies on Bangladesh rice farmers. For example, Gautam and Ahmed (2019) recently estimated the output elasticity of land, fertilizer, hired labor, additional costs, and farm capital at 0.71, 0.04, 0.08, 0.125, and 0.01, respectively. The elasticity of farm capital in organic fertilizer users was found negative and significant, and this implies that a 1% increase in farm capital will decrease rice output by 2.1%. This suggests that farmers should be careful when choosing farm assets to invest in and reduce rice output due to excess investment in farm assets. Moreover, negative and significant effect indicates that the marginal productivity of farm capital decreases in rice production.

### Table 4. Parameter estimates of maximum-likelihood for SPF model.

| Variable                        | Unmatched sample | Non-user | Matched Non-user |
|---------------------------------|------------------|----------|------------------|
|                                 | User             | Non-user | Matched Non-user |
|                                 | Coeff. S.E       | Coeff. S.E | Coeff. S.E      |
| Constant                        | 6.044 0.064***   | 6.595 0.074*** | 6.430 0.058***  |
| Land                            | 0.845 0.060***   | 0.662 0.041*** | 0.635 0.065***  |
| Labor                           | 0.044 0.059      | 0.065 0.039  | -0.025 0.065    |
| Fertilizer cost                 | 0.079 0.035**    | 0.108 0.025*** | 0.169 0.039***  |
| Other cost                      | 0.002 0.038      | 0.195 0.030*** | 0.181 0.039***  |
| Farm capital                    | -0.021 0.011***  | 0.043 0.009*** | -0.016 0.012    |
| Land^2                          | 0.223 0.050***   | 0.201 0.025*** | 0.113 0.055**   |
| Labor^2                         | 0.125 0.064**    | 0.046 0.035   | 0.056 0.070     |
| Fertilizer^2                    | 0.009 0.007      | 0.010 0.004*** | 0.011 0.008     |
| Other costs^2                   | 0.053 0.014***   | 0.063 0.012*** | 0.094 0.016***  |
| Farm capital^2                  | -0.003 0.002*    | 0.006 0.001*** | -0.002 0.002    |
| Land × Labor                    | -0.297 0.093***  | -0.123 0.045** | -0.052 0.101    |
| Land × Fertilizer               | 0.156 0.038***   | 0.028 0.020   | 0.137 0.043***  |
| Land × Other costs              | -0.156 0.050***  | -0.202 0.038*** | -0.167 0.056*** |
| Land × Farm capital             | 0.013 0.012      | -0.019 0.009** | 0.025 0.014*    |
| Labor × Fertilizer              | -0.082 0.048*    | 0.016 0.020   | -0.079 0.054    |
| Labor × Other costs             | 0.065 0.058      | 0.022 0.040   | -0.035 0.066    |
| Labor × Farm capital            | -0.005 0.014     | 0.002 0.009   | -0.016 0.016    |
| Fertilizer × Other costs        | -0.080 0.032***  | -0.019 0.017  | -0.056 0.036    |
| Fertilizer × Farm asset         | 0.009 0.007      | 0.001 0.004   | 0.016 0.008**   |
| Other cost × Farm capital       | -0.029 0.009***  | 0.017 0.006*** | -0.041 0.010*** |
| Aman rice                       | 0.197 0.038***   | 0.134 0.033*** | -0.029 0.043    |
| Boro rice                       | 0.505 0.045***   | 0.336 0.039*** | -0.053 0.050    |
| HYV                             | 0.119 0.046***   | 0.068 0.040*  | 0.076 0.044*    |
| Hybrid                          | 0.329 0.066***   | 0.086 0.062   | 0.136 0.075*    |
| Clay                            | 0.103 0.114      | -0.283 0.095*** | 0.151 0.117    |
| Loam                           | 0.127 0.056***   | -0.061 0.059  | -0.010 0.055    |
| Clay loam                      | 0.126 0.053**    | -0.159 0.057*** | 0.117 0.048**  |
| Sandy loam                     | 0.177 0.057***   | -0.056 0.060  | 0.150 0.053***  |
| AEZ-RT                          | 0.078 0.054      | 0.156 0.048*** | 0.147 0.059***  |
| AEZ-RHB                        | 0.305 0.067***   | 0.281 0.052*** | 0.467 0.075***  |
| AEZ-FP                         | -0.047 0.041     | 0.002 0.044   | 0.075 0.046    |
| AEZ-HP                         | 0.242 0.047***   | 0.118 0.051**  | 0.309 0.052***  |
| AEZ-MT                         | 0.111 0.062*     | 0.093 0.052*  | 0.247 0.066**   |
| AEZ-NEH                        | -0.103 0.046**   | 0.105 0.052**  | 0.007 0.047     |

**Variance and other model statistics**

- **Sigma (σ^2)**: 0.289 0.443 0.588
- **Gamma (γ)**: 0.555*** 0.801*** 0.747***
- **Log likelihood**: -816.58 -1276.20 -927.553
- **Returns to scale**: 0.9488*** 1.073*** 0.9436***

**Note:** "*, **, ***" show significance at the 10%, 5%, and 1% level.
square coefficient implies that the respective variable increase in double will increase rice output. Moreover, the positive and significant cross-terms in the SPF models imply that these inputs complement each other in increasing rice production, while negative and significant cross-terms in SPF models imply that increasing these variables decreases rice production.

Seasonal dummy shows that the organic fertilizer can increase 50% boro rice yield over aus rice. This may be the cause of yield difference which is consistent with Table 1. The contribution of high yield variety (HYV) and hybrid varieties is higher in organic fertilizer user than non-users. Furthermore, clay-loam and sandy-loam soil produce 13% and 18% higher yield than sandy soil for those who use organic fertilizer, while 12% and 15% higher produce yield who do not use organic fertilizer, respectively. This result confirms the importance of organic fertilizer. Moreover, organic fertilizer users in Bill and Haor Basin and Himalayan Plain zones produce rice 31% and 24% higher, while 11% lower respectively in Northeastern Hill region than Tidal Flood Plain agro-ecological zone.

4.4. Inefficiency model

The estimated results of the inefficiency variables in the SPF model are shown in Table 5. Farm size is positively significant with inefficiency for both groups indicates that small farms are found to be more efficient and efficiently use their resources than large farms, and large farms may waste their resources, which may be affected negatively associated with efficiency. Manjunatha et al. (2013) and Rahman (2003) also found a similar relation. Male farmers are positively associated with technical efficiency in all models except matched organic fertilizer non-user, which means male farmers may better manage than female farmers. We found the coefficient of education significantly positively associated with efficiency for organic users, suggesting that technical inefficiency increases with farmers' education level. It is due to the educated farmer's little engagement in farming practices as they have alternative income sources. The farm households engaged in wage work have positively and significantly associated with technical efficiency for organic fertilizer users indicating that they give more concentration in farm practices.

Land fragmentation has negative and significantly associated technical inefficiency, indicating that efficiency increases with the increase in the land piece for organic non-users. This may be because more fragmentation could reduce risk from natural disasters, stimulate crop diversification, and the easy allocation of labor over cropping seasons, suggesting that a higher number of land plots are more likely to diversify crops and could be used resources efficiently. However, land fragmentation makes a farmer inefficiency who use organic fertilizer. Land boundaries decrease the effective land size and more fragmentation makes more additional managerial bothers and may increase cost in the form of higher labour and transportation cost. Adoption of modern technologies is less likely to fragmented land. This result is consistent with Anik et al. (2017). Extension service positive and significantly increase technical efficiency for organic fertilizer user while decrease efficiency who do not use organic fertilizer. This result indicates that the extension service in adopting organic fertilizer is more important for increasing technical efficiency. The coefficient of family size is significantly positively associated with technical inefficiency because farm households need more money to maintain the family. Hence, farmers could not purchase farm inputs and technology as their requirement properly. Another cause may reflect the underemployment of family members. Long market distance influences to increase technical inefficiency due to long distances could be barriers to timely purchasing

| Table 6. Average treatment effect on treated (ATET) of organic fertilizer on rice yield. |
|---------------------------------|------------------|------------------|------------------|------------------|
|                                | Propensity score matching | Nearest neighbor matching | Inverse probability weight |
| Organic fertilizer users versus non-user | 598.08***    | 867.38***    | 724.29***    |
| Note: “*”, “**” and “***” indicate significance at the 10%, 5% and 1% level. |

| Table 7. Technical efficiency and predicted frontier yield before and after PSM. |
|---------------------------------|------------------|------------------|------------------|
|                                | User        | Non-user       | t-test of means difference (%) |
| Mean TE score (%)               | 74.46 (11.66) | 65.97 (15.53) | 12.87*** |
| Mean frontier yield             | 5780.4 (2475.6) | 6369.0 (3707.2) | -9.24*** |
| After PSM                       |               |                 |                 |
| Mean TE score (%)               | 74.46 (11.66) | 71.74 (12.08) | 3.79*** |
| Mean frontier yield             | 5780.4 (2475.6) | 5941.1 (2626.2) | -2.70 |
| Note: Parenthesis indicates standard deviation. Triple asterisks (*** ) indicate significance at the 1% level. |
inputs. However, access to credit facilities increases technical efficiency for non-users, and this is general for Bangladeshi farmers who are constrained by financial incapability. Anik et al. (2017) also found similar results. In the case of organic users, access to credit facilities reduces technical efficiency. This is because they did not use credit in farm practices.

4.5. Impact of organic fertilizer on yield and TE

The average effects of organic fertilizer on rice yield are calculated by comparing the yield between organic users and non-users. The average treatment effect on the treated (ATET) is estimated using Eq. (5), and the difference in the outcomes between the organic users and non-users is computed using the matched samples that is presented in Table 6. Table 6 revealed evidence of a statistically significant difference between the yield of organic fertilizer users and non-users. All of the signs of the ATETs in different matching are positive, indicating that the rice yield for organic fertilizer users is significantly higher than they are for non-users. Hence, our analysis indicates that the use of organic fertilizer had a positive effect on rice yield. This result is consistent with Villano et al. (2015).

The technical efficiency (TE) score and frontier predicted rice yield is estimated from organic fertilizer user and non-user by using SPF models for before and after PSM, shown in Table 7. The Table also compared and statistical t-test of the mean TE and predicted yield difference between organic fertilizer users and non-user. We found the TE significantly different between the groups for both unmatched and matched samples. The results revealed that organic fertilizer users and non-user operate at mean TE levels of 74.46% and 71.74% after sample selection, implying that farmers produce only 74.46% and 71.71% of the maximum attainable output for given input level, respectively. The result shows that organic fertilizer users significantly 3.79% higher efficient than non-user. However, it was 12.87% higher before sample selection correction.

How sample correcting for biases from observed variable affects technical efficiency levels, Figure 3 revealed a better understanding of the distribution of TE scores estimated by SPF for unmatched and matched samples for visual inspection.

Finally, Table 7 also represent that the yield differences between organic fertilizer user and non-user before and after selection bias correction have been examined to compare which group having a higher output. In this regard, we predict frontier yield produced from the matched and unmatched SPF models. Our results show that organic fertilizer non-user obtain a significantly 9.24% higher yield than organic fertilizer users without sample correction. After sample selection, although non-user produces higher yield due to lower efficiency but this is insignificant.

5. Conclusion

This study assessed the determinants of organic fertilizer choice and the impact of organic fertilizer on technical efficiency and rice yield in Bangladesh using data from 3253 plots. PSM is used to overcome self-selection biases associated with observed characteristics, allowing for unbiased and consistent estimation of the impact of organic fertilizer on yield and technical efficiency. The marginal effect revealed that age, education, family size, and the number of cattle had positive and significantly affected organic fertilizer choice, while farm size and distance to the nearest market had negative and significant effects on organic fertilizer choice. The results showed that organic fertilizer users got two types of benefits such as 6.3% higher yield of rice by applying 12.1%, 9.4%, and 42.1% less amount of labor, other inputs, and farm capital for rice production per hectare, respectively. However, the yield difference was found at 16.67% higher for users than non-user after sample selection. It implies that rice production is increasing due to increased soil fertility, with fewer chemical fertilizers and labor use. The elasticity of land is significantly 21% point higher for organic fertilizer users than non-user. The elasticity of labor is insignificant for both groups, indicating marginal productivity of labour decreasing and labour abundance in Bangladesh. The elasticity of chemical fertilizer is significantly higher for non-user than users, confirming that organic fertilizer users are more close to optimum use of fertilizer.

This study found that male farmers and extension service increases technical efficiency for organic fertilizer user. However, technical inefficiency increases with farmers’ education level, indicating educated farmers give less attention to farming as they have alternative income sources. Land fragmentation significantly increases efficiency increases for organic non-users. This is because more fragmentation could reduce risks from natural disasters and more likely to diversify crops where efficiently uses of resources. On the other hand, land fragmentation makes a farmer inefficient who use organic fertilizer because land boundaries decrease the effective land size and less opportunity to adopt modern technology. The average treatment effect on the treated (ATETs) in different matching is positive and significant, indicating that the rice yield for organic fertilizer users is higher than non-users. This study found that the TE significantly different between the groups, and the results revealed that organic fertilizer users significantly 3.79% higher efficient than non-user.

Positive and significant increased rice yield by using organic fertilizer, which supports less requirement of chemical fertilizer. It motivates farmers to increase the use of organic fertilizer for enhancing production and sustainable fertility management of soil. This study argues that organic fertilizer users have significantly higher efficiency than non-user. Government and non-government organizations should come forward to strengthen organic fertilizer use through extension services for sustainable agricultural development. Since the farmers of Bangladesh are not aware of using organic fertilizer, the extension service could play a vital role in promoting and using organic fertilizer. So, need-based extension services should be ensured with the current agricultural development policies of Bangladesh. The government should encourage the public and private sectors by providing an appropriate capacity-building program. In this
case, the government, as well as the private sector, should come forward to the commercialization of organic fertilizer for easy access to farmers.

Declarations

Author contribution statement

Md Abdus Salam: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.
Md Nazirul Islam Sarker: Performed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.
Sajia Sharmin: Contributed reagents, materials, analysis tools or data.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

References

Abd El-Mageed, T.A., El-Samoudi, I.M., Ibrahim, A.E.A.M., Abd El Tawwab, A.R., 2018. Compost and mulching modulates morphological, physiological responses and water use efficiency in sorghum (bicolor L. Moench) under low moisture regime. Agric. Water Manag. 208 (February), 431–439.
Abdul-Rahaman, A., Abdulai, A., 2018. Do farmer groups impact on farm yield and efficiency: a case of Bangladeshi farmers. Open Agri. 3 (1), 567–577.
Abd El-Mageed, T.A., El-Samnoudi, I.M., Ibrahim, A.E.A.M., Aba El Tawwab, A.R., 2018. Impact of compost and mulching on water use efficiency and yield of crops with nutrient-enriched organic fertilizer at dry and wet season in ensuring climate-smart agriculture. Int. J. Recycl. Org. Waste Agric. 8 (11), 81–92.
Abdel-Mageed, T.A., El-Samnoudi, I.M., Ibrahim, A.E.A.M., Abd El Tawwab, A.R., 2018. Assessment of heavy metals in foods around the industrial areas: health hazard inference in Bangladesh. Geocarto Int. 35 (3), 280–295.
Abel, M.H., Melese, K.A., 2018. Impact of off-farm activities on technical efficiency: evidence from maize producers of eastern Ethiopia. Afri. Food Econ. 6 (1).
Abdel-Mageed, T.A., El-Samnoudi, I.M., Ibrahim, A.E.A.M., Aba El Tawwab, A.R., 2018. Impact of compost and mulching on water use efficiency and yield of crops with nutrient-enriched organic fertilizer at dry and wet season in ensuring climate-smart agriculture. Int. J. Recycl. Org. Waste Agric. 8 (11), 81–92.
Abdel-Mageed, T.A., El-Samnoudi, I.M., Ibrahim, A.E.A.M., Aba El Tawwab, A.R., 2018. Assessment of heavy metals in foods around the industrial areas: health hazard inference in Bangladesh. Geocarto Int. 35 (3), 280–295.
Abdel-Mageed, T.A., El-Samnoudi, I.M., Ibrahim, A.E.A.M., Abd El Tawwab, A.R., 2018. Assessment of heavy metals in foods around the industrial areas: health hazard inference in Bangladesh. Geocarto Int. 35 (3), 280–295.
Abdel-Mageed, T.A., El-Samnoudi, I.M., Ibrahim, A.E.A.M., Abd El Tawwab, A.R., 2018. Assessment of heavy metals in foods around the industrial areas: health hazard inference in Bangladesh. Geocarto Int. 35 (3), 280–295.
Abdel-Mageed, T.A., El-Samnoudi, I.M., Ibrahim, A.E.A.M., Abd El Tawwab, A.R., 2018. Assessment of heavy metals in foods around the industrial areas: health hazard inference in Bangladesh. Geocarto Int. 35 (3), 280–295.
Abdel-Mageed, T.A., El-Samnoudi, I.M., Ibrahim, A.E.A.M., Abd El Tawwab, A.R., 2018. Assessment of heavy metals in foods around the industrial areas: health hazard inference in Bangladesh. Geocarto Int. 35 (3), 280–295.
AbDEL-MAGEED, T.A., EL-SAMNOUDI, I.M., IBRAHIM, A.E.A.M., ABA EL TAWWAB, A.R., 2018. Impact of compost and mulching on water use efficiency and yield of crops with nutrient-enriched organic fertilizer at dry and wet season in ensuring climate-smart agriculture. Int. J. Recycl. Org. Waste Agric. 8 (11), 81–92.