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Sustainable Feasibility of the Environmental-Friendly Policies on Agriculture and Its Related Sectors in India

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Abstract: In terms of economic development and feeding the world's populations, the importance of the agricultural sector is well known. However, agriculture and its related sectors are also known for contributing more than one-quarter of the world's GHG emissions. To address this issue, we evaluate the performance of agriculture and its related firms in India from 2013 to 2019 with its environmental efficiency under the paradigm shift promoted by the National Agroforestry Policy in 2014. To evaluate the feasibility of this paradigm shift in agricultural policy, the non-radial slack-based measure (SBM) is utilized in the first stage, and Tobit regressions are used to assess the determinants of efficiency (or sources of inefficiency) measures at the second stage. The results from non-radial SBM show that Indian agricultural firms (foreign direct investment, private, and public) show huge potential with 32.2% on average to enhance their performance if they move toward the frontier of the production possibility curve. This suggests that Indian policymakers should regulate much stronger regulations for firms, especially for the use of agricultural inputs such as energy (fertilizers), with performance-oriented financial measures for sustainable agriculture. To determine the strategic variables for these firms to enhance their performance, Tobit regressions showed that fertilizers use (−3.350%) appears to have the highest negative impact on environmental efficiency. On the other hand, credit access (2.710%) has the highest positive impact on environmental efficiency, implying that policymakers should provide subsidies to firms in the form of soft loans (or credit access) for the purchase of high-quality fertilizers and to adopt energy-saving equipment/technology to minimize the use of chemical fertilizers in India.

Keywords: environmental efficiency; non-radial slack-based measure; Tobit regression; agriculture; India

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1. Introduction

Agriculture is the main engine for economic development and feeding the world's population in many countries. According to the World Bank, 65% of working poor adults made their living from agriculture in 2016 [1]. In the Indian economy, agriculture contributes to about 20% of the national gross domestic product (GDP), while about 58% of the Indian population depends on agriculture for their livelihood, directly or indirectly [2,3]. Figure 1 shows the trend of India's GDP coupling with agriculture and its related sector value-added (ARS-VA) from 2000 to 2019 [4,5]. From Figure 1, it can be seen that there is a significant coupling relationship between GDP and ARS-VA in India. When there is an increase in the growth of Indian GDP, there is also an increase in the number of ARS-VAs, which indicates that the agriculture sector plays an important role in boosting Indian GDP. However, even though there is a direct relationship between India's GDP and ARS-VA, the agriculture sectors are also known as major emitters of greenhouse gases (GHGs) into the atmosphere after the energy sectors. Figure 2 shows GHG emissions by sector in India from 2000 until 2018 (in Million Ton) [6]. It shows that after the energy sectors, the agricultural sector is the second-largest emitter of GHGs in 2018, with 22.63% (including

Land-Use Change and Forestry), implying that the agricultural sector should also be a major target in the GHG emission abatement. India is also the third-largest emitter of GHGs after China and the United States, and thus, Indian agriculture is exposed to stresses resulting from climate change due to emissions from agriculture and its related sectors. The increasing use of agricultural inputs (such as large amounts of energy consumption in the form of electricity, machinery, diesel fuel, fertilizers, human labor, etc.) used in agricultural production is the main driver of increasing GHG emissions in developing countries like India. Hence, we can say that the agricultural sectors also play a major role in the degradation of the Indian environment.

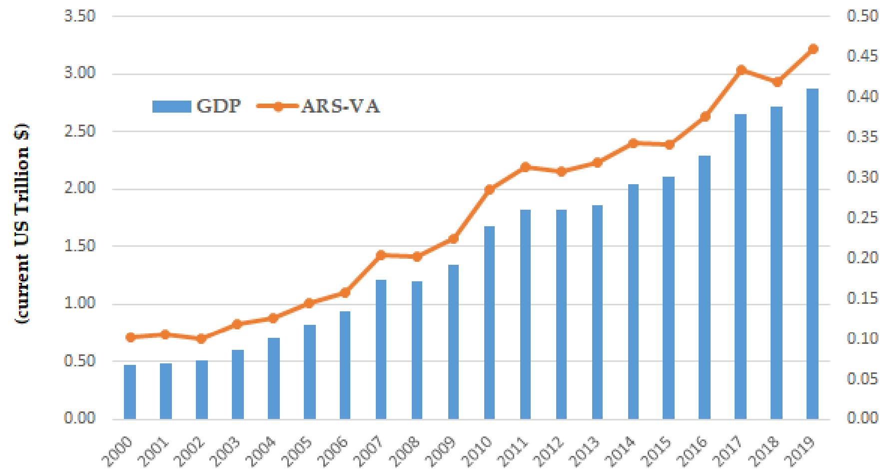

Figure 1. Trends of India's GDP and ARS-VA from 2000–2019.

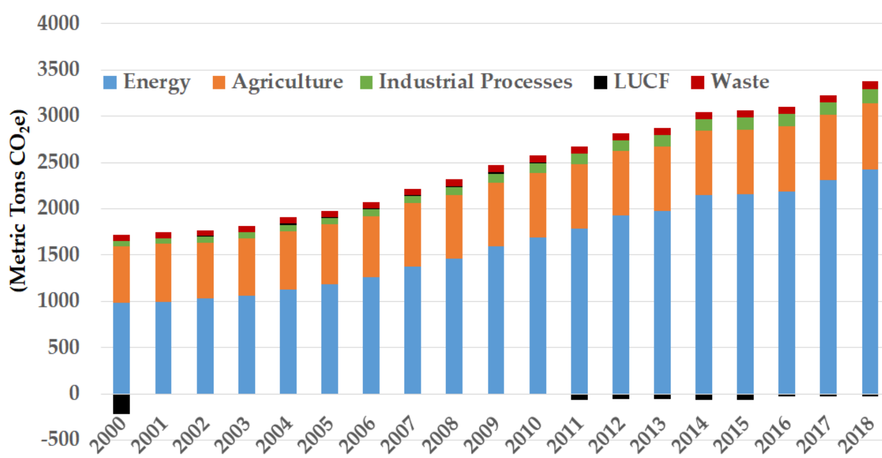

Figure 2. Sector-wise GHG emissions in India from 2000 to 2018.

Some studies on climate change have indicated that developing countries may be more disadvantaged than developed countries as the agricultural sector is under considerable pressure to identify the most effective climate change mitigation policies and measures [7,8]. India is not an exceptional case in this emerging new norm of environmental issues. Due to this global pressure, the agricultural sectors have been at the forefront of the UNFCCC negotiations since 2007, held at the Conference of Parties (COP 13) in Bali, Indonesia [9]. Mitigation in the agricultural sector and reducing greenhouse gas emissions while using limited energy resources are part of climate challenges to reduce environmental problems and increase agricultural sustainability. To fulfill the ambitious commitment to the international treaty of the UNFCCC, the creation of sustainable and climate-resilient agricultural systems has been put forward as part of India's plan to reduce the emission intensity of its GDP by 35% by 2030, compared to 2005 levels. Meanwhile, India's National Agroforestry Policy aims to improve agricultural livelihoods to mitigate climate change by maximizing agricultural productivity. This policy was launched by the Indian government in February 2014, in which India became the first country in the world to adopt such a policy in agriculture sectors [10]. This policy also improves productivity and environmental sustainability by integrating crops, trees, and livestock in the same land plot. Nonetheless, this paradigm shift in the agriculture industry may not be strong enough for the industry/firms to improve its efforts for GHG abatement.

Based on the above discussion, this research aims to evaluate the environmental efficiency of agriculture and its related sectors in India to evaluate the feasibility of India's National Agroforestry Policy in 2014. Here, the environmental efficiency in this study is referring to the mitigation of the GHGs generated from agriculture and its related sectors in India. For this research objective, this paper seeks to address the following research questions based on the applied Indian policy mention in our study**:** Is India's agricultural sector performance sustainable in terms of environmental efficiency? Has the Indian agricultural sector's environmental efficiency changed in recent years based on the above policy applied? What are the main sources of inefficiency, and is there a way to improve the efficiency of the agricultural and its related sector in India? This study will not only help Indian farmers and policymakers but will also contribute to the interest of other developing countries to tackle GHG emissions from agriculture and its related sectors.

The structure of the article is as follows: Section 2 presents a review of the literature on the conceptual research model and variables of previous studies in the agricultural sector; Section 3 develops empirical models to assess the environmental efficiency of agriculture and its related sectors at the firm level in India; Section 4 gives descriptions about the data sources, then discusses the empirical result and its implications. Finally, Section 5 concludes the study by providing policy implications and suggestions regarding agricultural GHG emissions in India.

2. Conceptual Research Model and Variables

There is a wide variety of existing studies that assess the efficiency of agricultural sectors. Most of these studies use data envelopment analysis (DEA) applications when multiple inputs and outputs are considered simultaneously [11,12]. For example, Khoshroo et al. [11] studied the efficiency of turnip farms in Iran. The DEA model was applied with input variables like labor, machinery, seeds, fertilizer, and irrigation as well as desirable and undesirable output of turnip and emissions. On the other hand, Cecchini et al. [12] used livestock, labor, feed, an agricultural area, and capital as inputs variables and considered milk and CO_2-eq as desirable and undesirable variables by adopting a slack-based measure of DEA (SBM-DEA) with undesirable output to quantify the marginal CO_2 reduction costs of dairy cattle farms in Italy.

Since the traditional DEA model takes a radial approach, which might ignore slack variables and result in overestimation and low discriminating power, SBM-DEA has been widely used as an alternative to traditional DEA to capture the whole aspect of inefficiency in terms of input and output slacks in the efficiency measures. [12–14]. Therefore, in this study, we use the SBM-DEA with undesirable output to determine our study of efficiency evaluation. To calculate efficiency using the SBM-DEA model, we first need to identify the possible number of input and output variables. Considering the existing studies in Table 1, we have selected three input variables as employee, capital, and energy; one desirable output variable as sales turnover; and one undesirable output variable as GHG emissions.

Table 1. Research on the application of DEA and its integration with other models in the agricultural sector.

Author(s) (Year)	Field of Application	First-Stage		Second-Stage	
		Variables	Method	Variables	Method
Kuang et al. (2020) [15]	CLUE for 31 provinces in China from 2000 to 2017.	Land, labor, machinery, fertilizers, pesticides, plastic film, irrigation, gross agricultural production, output of grain, and carbon emissions.	SBM-DEA	Natural condition, cultivated land resource endowments, agricultural production condition, regional economic development, and regional science and technology development.	Tobit model
Horvat et al. (2019) [16]	Technical efficiency for 25 Serbian districts.	Utilized agricultural area, livestock, labor, and economic size.	Two-stage DEA	Utilized agricultural area, irrigated agricultural area, education, years, and DEA efficiency scores.	Tobit model
Yan (2019) [17]	Efficiency for agricultural enterprises	Total assets, operating costs, management costs, and profit.	DEA	Age, size, ROA, ownership concentration, nature of controlling shareholders, and Crste.	Tobit model
Raheli et al. (2017) [18]	Efficiency for tomato farming in East Azerbaijan province, Iran.	Labor, machinery, fertilizers, biocides, seed, diesel fuel, water for irrigation, and tomato.	DEA	Age, area, education, and manure.	Fractional regression
Vlontzos et al. (2017) [19]	Eco-(in)efficiency index for EU agricultural sector from 1999–2012.	Land, energy, chemicals and fertilizers, fixed capital, labor, output, and GHG Emissions.	DEA	Eco-efficiency, Energy, GHG emissions	Regression Model
You et al. (2016) [20]	Eco-efficiency for 31 provinces in China.	Labor, machinery, pesticide, diesel oil, ammonia nitrogen emission, total nitrogen emission, and total phosphorus emission.	Input-oriented DEA	Education, farmland area, income, wage, population, population burden, fixed assets, agriculture's position, and industrialization level.	Tobit model
Ray (2014) [21]	Technical efficiency for individual states over the years 1970–71 to 2000–01.	Land, fertilizers, irrigated area, pump sets, tractors, electricity, labor, rainfall, food grains and nonfood grains.	DEA	Land, degree of openness, education and research, credit, crop diversification index, literacy rate, gross cropped area, irrigated area, annual rainfall, input, output, and Pareto–Koopmans efficiency.	Regression Model
Hansson (2008) [22]	Efficiency for dairy farms in Sweden.	Fodder, labor, capital, energy, seed, fertilizer, milk, livestock, crops, forage, and "other".	DEA	Personal aspects, management systems, farm performance, efficiency scores, aspects of the management systems.	Logistic and Tobit regression

Based on our results of the SBM-DEA model, we obtain the efficiency score of agriculture and its related firms. However, to enhance the efficiency of these firms, we need to find out the determinants of efficiency measures; for this, we need a second stage of evaluation. In our model, we use the efficiency scores as the dependent variable, wherein dependent variables have some limits because efficiency never has the negative side of the value. Thus, due to this limited approach to dependent variables, the ordinary least square (OLS) model may give the estimate of a biased parameter [23], and thus most of the previous literature took the Tobit model as the role model [15–17]. The Tobit model also has the advantage of avoiding bias and inconsistencies when estimating unknown parameters with censored or limited variables, making it a more reliable choice to assess the determinants of environmental efficiency [14]. Kuang et al. [15] adopted the SBM model with undesirable outputs to analyze carbon emissions resulting from cultivated land-use efficiency in China. Along with the SBM model, they also employed a Tobit regression model to determine their study. In order to use this Tobit model, we need to select a second stage of the variables; similarly, different authors selected several variables for the DEA model and the Tobit regression, separately, for the evaluation of efficiency and to measure the determinants of efficiency measures in agricultural sectors at the same time [15–17,19,21]. Combining with the existing studies (Table 1), we believe that land [15], livestock [12], fertilizer [11], agricultural cultivation [15], urbanization rate [15], average rainfall [24], economics openness—export [25], and credit access [26] will have an influence on India's agriculture and its related sectors. Therefore, we use these eight explanatory variables for the Tobit model.

Some authors have already analyzed the efficiency of agricultural sectors at the firm level in their host country [17,18,21]. However, to the best of our knowledge, there is limited study on the environmental efficiency of agriculture and its related sectors at the firm level in India as firms can represent a main source of GHGs globally. Therefore, to fill the research gap, we assess agriculture and its related sector's environmental efficiency in India, based on firm-level data from 2013–2019.

3. Material and Methods

3.1. SBM-DEA Model with Undesirable Outputs

To estimate the environmental efficiency, there were many advantages to using DEA techniques, such as using DEA with undesirable output [16]. There are two types of DEA models, which can be categorized as radial and non-radial models. The SBM-DEA method of the non-radial and non-oriented approach is widely adopted, in which slacks of input and output are used to generate an efficiency estimate directly. The radial approach's inputs and outputs may lack information regarding the inactive (or neglected) efficiency of the inputs or outputs involved in the production process adjusted to the efficiency goal in the same proportion [27]. On the other hand, to classify and compare decision-making units (DMUs), the non-radial efficiency approach uses the slack variable, which results in a stronger discriminatory power and an unbiased estimate. As our study focuses on the precise and discriminating assessment of environmental performance at the firm level of agriculture and its related sectors, we use the SBM-DEA with an undesirable output for the empirical study [12,13,15].

Let us assume that we have n decision-making units (DMUs), and each DMU consumed m inputs, which produced g_1 desirable (good) output and b_2 undesirable (bad) output. For DMU_i, the vectors of three factors can be defined as $X \in R^m$, $Y^g \in R^{g_1}$, and $Y^b \in R^{b_2}$, respectively. Then, the matrices X, Y^g, and Y^b are specified as follows [13]: $X = [x_1, x_2, \ldots, x_n] \in R^{m \times n}$, $Y^g = y_1^g, y_2^g, \ldots, y_n^g, \in R^{g_1 \times n}$, and $Y^b = y_1^b, y_2^b, \ldots, y_n^b, \in R^{b_2 \times n}$, where X, Y^g, and $Y^b > 0$. Therefore, the SBM-DEA production technology under the constant returns to scale (CRS) of the production possibility set (P) can be described in Equation (1) as follows [23]:

$$P = \left\{(X, Y^g, Y^b)\right\} \mid x \geq X\lambda,\ y^g \leq Y^g\lambda,\ y^b \geq Y^b\lambda,\ \lambda \geq 0\} \quad (1)$$

Now, the SBM-DEA model with undesirable outputs can be described in Equation (2) as follows [28];

$$p^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{g_1 + b_2}\left(\sum_{r=1}^{g_1}\frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{b_2}\frac{s_r^b}{y_{r0}^b}\right)} \quad (2)$$

$$\text{s.t.} \begin{Bmatrix} x_0 = X\lambda + s^-; y_0^g = Y^g\lambda - s^g;\ y_0^b = Y^b\lambda + s^b \\ s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0 \end{Bmatrix}$$

λ= the non-negative weight vector,

s^- and s^b= the overuse of inputs and undesirable outputs,

s^g= the shortage of desirable outputs,

0= the estimated DMU in the current model, respectively.

If and only if $\varrho^* = 1$, then the DMU (firm) is considered to be efficient when all the slack variables are zero ($s^{-*} = s^{g*} = s^{b*} = 0$), even if there are undesirable outputs, and vice-versa for $\varrho^* < 1$. However, if firms are to become environmentally efficient, that is, to mitigate the GHGs generated from agriculture and its related sectors in India at the firm level, they must eliminate excess inputs and undesirable output while increasing and adjusting the deficit of desirable output. Here, inputs refer to the firm's employees, capital, and energy consumption; undesirable output related to GHG emissions generated by the firm; and the desirable output relating to the firm's sales turnover.

3.2. Tobit Regression Model

After we obtained the environmental efficiency of sample firms based on SBM-DEA, we used the regression model to analyze the determinants of environmental efficiency of sample firms as a second stage. As the residuals' expected value is necessarily zero in the OLS hypothesis, it may yield inconsistent or biased estimates when applying OLS on censored or truncated data [29]. Especially since the value of efficiency measures is between 0 and 1 in the SBM-DEA model with undesirable output, the traditional OLS estimation is not favorable for testing the determinants of environmental efficiency [15]. Therefore, the Tobit model is more popular for solving this methodological problem at the second stage with the efficiencies based on the DEA approach [15–17,19,21]. In a two-stage analysis procedure, the Tobit model is generally applied in efficiency literature [30–33]. Therefore, based on the Tobit regression approach, we can define the econometric model in Equation (3) as [26]:

$$Y_{np} = \begin{Bmatrix} Y_{np} = \beta^T x_{np} + \epsilon_{np} \;\; \beta^T x_{np} + \epsilon_{np} \\ 0 \text{ otherwise} \end{Bmatrix} \tag{3}$$

Y_{np}= the explained variable,
x_{np}= the explanatory variable,
β^T= the vector of the regression coefficient of the explanatory variable,
ϵ_{np} = the stochastic error assumed to follow the distribution of $N(0, \sigma^2)$, respectively.

To assess the factors influencing inefficiency in agriculture and its related sectors, the Tobit model can be defined in Equation (4) as [29]:

$$Y_{np} = \beta_0 + \beta_1 Z^1{}_{np} + \beta_2 Z^2{}_{np} + \beta_3 Z^3{}_{np} \; \ldots, \; \beta_x Z^X{}_{np} + \epsilon_{np} \tag{4}$$

Y= the efficiency measure (or environmental efficiency of sample firms),
np= the n^{th} firms of sample study and the year or period of study,
β_x= the coefficient,
$Z^X{}_{np}$ = the explanatory variable,
ϵ_{np}= the stochastic error, respectively.

4. Data Collection and Empirical Results

As this study aims to analyze the firms' environmental efficiency of agriculture and its related sectors in India, we collected data (56 firms) from 2013 to 2019. The sector in this study includes the following sub-sectors: dairy products, consumer goods and products, agri-food products, food and beverages, food production, fertilizers, agriculture, sugar, agrochemicals, agro-industry, farming, fishery, tea and coffee, and poultry and livestock.

4.1. Input and Output Variables

As mentioned in Section 2, we choose the three basic input variables; capital, employee, and energy consumption. As for outputs, sales turnover (desirable output) and GHG emissions (undesirable output) were considered. We extracted all the data from each firm's annual report provided on each firm's webpage. Regarding the capital input, we took into account the data on the firm's fixed assets published each year by the firm in their annual report, from 2013–2019. Likewise, for the employees' input, we choose the employees per head of each firm provided by the firm every year. Usually, in agriculture and its related sectors, researchers consider different types of desirable output, such as net value-added, agricultural production or agricultural output, profitability, etc. However, our research sample is based on firm-level data, so we use the firms' sales turnover, which is equivalent to the other desirable outcome. For sales turnover output, we have considered the revenue generated from the operations by the firms each year from 2013 to 2019. On the other hand, we collected the energy input and GHG emission output values using the macro level of agriculture and its related firms' data of power and fuel consumption rate provided by the firm in each year [34]. In case a firm did not provide the direct amount of energy it consumed and the direct amount of CO_2 equivalent of GHGs it produced during the year, we then convert the power and fuel consumption rate into total energy consumption and CO_2 equivalent of GHG emissions. All the descriptive statistics of input and output variables are shown in Table 2.

In India, there are three types of firms in the agricultural sectors: private, public, and foreign direct investment (FDI) firms (Table 2). Each group of firms may respond differently to the regulatory policies of the government on the agriculture sectors, and thus may result in more precise implications and customized suggestions in our research. It is, therefore, important to analyze these three types of firms and assess their performance in terms of sustainable agriculture [35]. According to the reports [36], to launch India's GHG Program, representatives from some firms, including Bayer Group from FDI group and Tata Chemicals from a private local group and its related sectors, have joined the environmentalist and government leaders to foster sustainable profitability competitive firms. On this basis, we compare the performance between FDI, private firms, and public firms to assess these firms' environmental efficiency and see if there is a difference between these groups in the patterns of environmental efficiency.

Table 2. Descriptive statistics of input and output variables from 2013–2019.

Firm	Variable (Unit)	Input/Output	Mean	Std. Deviation	Maximum	Minimum
FDI	Employee (Per person)	Input	2433.381	2133.565	7649.000	252.000
	Capital (Million rupees)	Input	8655.340	10,616.070	47,160.000	524.340
	Energy (Gj)	Input	342,959.633	408,573.477	1,522,000.000	6368.390
	Sales turnover (Million rupees)	Desirable output	57,201.725	77,509.104	388,880.000	4593.300
	GHG emissions (Tons)	Undesirable output	12,775.394	14,428.415	54,417.650	227.670
Private	Employee (Per person)	Input	1557.024	1551.181	5173.000	177.000
	Capital (Million rupees)	Input	2591.291	3645.471	16,409.580	150.000
	Energy (Gj)	Input	10,355.371	11,937.045	47,663.470	1881.650
	Sales turnover (Million rupees)	Desirable output	94,946.336	152,120.579	741,000.000	2270.280
	GHG emissions (Tons)	Undesirable output	4323.290	8289.132	47,312.370	81.160
Public	Employee (Per person)	Input	1066.837	1100.962	5077.000	6.000
	Capital (Million rupees)	Input	129,638.839	764,029.248	5,652,745.300	12.630
	Energy (Gj)	Input	2,420,438.986	12,638,523.524	83,526,299.200	337.800
	Sales turnover (Million rupees)	Desirable output	498,961.030	1,607,358.846	10,305,640.400	2306.730
	GHG emissions (Tons)	Undesirable output	35,916.885	119,537.804	729,131.140	116.140

Based on Table 3, the correlation between the firms' input and output variables is almost significantly positive. This means that the output values will increase or decrease depending on the input usage during the production process. Both employee and capital are positively correlated with sales turnover because they are the representative variables to explain production. On the other hand, there is a significant relationship between capital and energy consumption, which indicates that when the firm purchases and upgrades energy-saving equipment, it will also affect its energy consumption in question [37]. While the GHG emissions show a positive relationship for energy input and sales turnover output, energy and GHG emissions show a very significant relationship [34]. Therefore, we can conclude that this formulation is appropriate when analyzing the data from an environmental point of view.

Table 3. Correlation Matrix of input and output variables.

Variables	Employee	Capital	Energy	Sales Turnover	GHG Emissions
Employee	1.000				
Capital	0.297	1.000			
Energy	0.324	0.964	1.000		
Sales turnover	0.300	0.368	0.362	1.000	
GHG emission	0.412	0.367	0.915	0.874	1.000

4.1.1. Environmental Efficiency of Indian Agriculture and Its Related Firms

Based on Equations (1) and (2), Table 4 illustrates the environmental efficiency of 56 Indian agricultures and its related firms for seven consecutive years (2013–2019). As discussed in Section 4.1, we classified sample firms into three types—FDI, private, and public firms in India—and compare their environmental efficiency. Due to privacy concerns, we used the firm's identification (id) name as equivalent to the firm's name. The overall environmental efficiency scores range from 0.156 to 1, and the average of FDI, the private firms, and the public firms is approximately 0.609, 0.569, and 0.675, respectively. This implies that 39.1% of the FDI firms, 43.1% of the private firms, and 32.5% of the public firms can be obtained if they are located on the frontier. Among 56 firms, ALIL, a public firm, is the only firm showing environmental efficiency score of 1, indicating that ALIL adjusts to the environmental regime very well. This result stems from that ALIL has already reviewed their performance in implementing the policy, annually and periodically, and updated it as needed to be an integral part of the Indian environmental sustainability vision**.** As expected, public firms make more efforts to adopt the paradigm shift of the policies. While the highest efficiency scores among FDI and private firms in 2019 are BI and BRL, respectively, compared to ALIL, these firms still need an efficiency increase of 14.7% and 15.4% to reach their target. The reason could be that FDI firms are insensitive and not proactive in implementing local regulatory policies in the host country. Meanwhile, Indian firms (especially private firms) are more interested in hassle-free short-term gains other than a long-term vision like the national agroforestry policy [38]. As a result, firms opt for short-period, benefit-related policies in India, which could lead to unsustainable policy implementation and lead to environmental degradation among FDI and private firms.

Table 4. Environmental efficiency of agriculture and its related firms (2013–2019).

Firms Id	Firm Type	2013	2014	2015	2016	2017	2018	2019	Average
AFL	FDI	0.457	0.594	0.697	0.781	0.811	0.873	0.865	0.725
BIL	FDI	0.340	0.377	0.376	0.481	0.621	0.743	0.878	0.545
BI	FDI	0.776	0.675	0.630	0.849	0.882	0.852	0.853	0.788
BIL	FDI	0.557	0.560	0.611	0.786	0.879	0.820	0.817	0.719
CIL	FDI	0.406	0.416	0.522	0.631	0.709	0.823	0.842	0.621
DAL	FDI	0.536	0.524	0.532	0.604	0.704	0.837	0.876	0.659
ECCL	FDI	0.319	0.455	0.445	0.506	0.708	0.836	0.850	0.588
GSCHL	FDI	0.436	0.478	0.498	0.599	0.699	0.702	0.843	0.608
GAL	FDI	0.314	0.406	0.418	0.594	0.628	0.815	0.825	0.571
HUL	FDI	0.417	0.495	0.401	0.681	0.750	0.939	0.851	0.648
IIL	FDI	0.251	0.279	0.384	0.488	0.506	0.701	0.804	0.488
MIL	FDI	0.325	0.478	0.473	0.560	0.677	0.869	0.863	0.606
NIL	FDI	0.235	0.252	0.337	0.460	0.686	0.613	0.737	0.474
RIL	FDI	0.270	0.289	0.393	0.461	0.503	0.598	0.712	0.461
TP&GC	FDI	0.410	0.494	0.515	0.628	0.737	0.776	0.843	0.629
AFF	Private	0.293	0.468	0.491	0.411	0.687	0.870	0.854	0.582
AAL	Private	0.298	0.340	0.420	0.489	0.766	0.815	0.900	0.575
BRL	Private	0.427	0.374	0.452	0.457	0.707	0.838	0.846	0.586
HAPL	Private	0.380	0.355	0.387	0.405	0.676	0.844	0.847	0.556

KSCL	Private	0.322	0.376	0.439	0.495	0.657	0.875	0.852	0.574
ML	Private	0.283	0.311	0.388	0.390	0.684	0.862	0.871	0.541
ALIL	Public	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
CCL	Public	0.410	0.449	0.608	0.707	0.856	0.869	0.945	0.692
DSML	Public	0.276	0.380	0.757	0.806	0.806	0.820	0.922	0.681
DDL	Public	0.376	0.289	0.566	0.619	0.707	0.794	0.850	0.600
DSIL	Public	0.256	0.248	0.464	0.630	0.693	0.728	0.786	0.544
FCL	Public	0.368	0.283	0.475	0.611	0.670	0.733	0.880	0.574
GOL	Public	0.530	0.799	0.880	0.853	0.857	1.000	0.952	0.839
HFL	Public	0.327	0.317	0.550	0.657	0.774	0.857	0.724	0.601
ISL	Public	0.200	0.278	0.444	0.596	0.662	0.674	0.750	0.515
KSML	Public	0.325	0.392	0.642	0.657	0.787	0.753	0.837	0.628
KI	Public	0.755	0.823	0.902	0.928	0.928	1.000	1.000	0.905
KL	Public	1.000	1.000	0.973	0.905	0.893	0.875	0.808	0.922
LCCL	Public	0.312	0.468	0.505	0.736	0.850	0.827	0.815	0.645
MFL	Public	1.000	1.000	0.632	0.763	0.803	0.738	0.750	0.812
MC&FL	Public	0.625	0.324	0.397	0.516	0.691	0.602	0.725	0.554
NIL	Public	0.246	0.245	0.273	0.570	0.714	0.709	0.711	0.495
NS	Public	0.307	0.386	0.550	0.764	0.806	0.816	0.808	0.634
OFL	Public	0.935	1.000	0.860	0.966	0.926	0.835	0.895	0.917
PMFL	Public	0.259	0.270	0.419	0.517	0.724	0.819	0.839	0.550
PSL	Public	0.156	0.265	0.347	0.481	0.673	0.719	0.824	0.495
RPL	Public	0.420	0.481	0.425	0.722	0.820	0.822	0.883	0.653
HGAIL	Public	0.336	0.317	0.454	0.653	0.721	0.803	0.870	0.593
SFL	Public	0.665	0.675	0.790	0.872	0.863	0.855	0.851	0.796
SSLEL	Public	0.251	0.547	0.652	0.873	0.889	0.864	0.825	0.700
SEPEL	Public	0.312	0.257	0.395	0.590	0.766	0.713	0.805	0.548
SPICL	Public	0.236	0.301	0.486	0.668	0.837	0.881	0.840	0.607
TCL	Public	0.762	0.363	0.449	0.653	0.808	0.830	0.816	0.669
TCPL	Public	0.525	0.648	0.514	0.723	0.889	0.889	0.888	0.725
TF&CTL	Public	0.414	0.798	0.430	0.651	0.797	0.768	0.814	0.667
TUSWL	Public	0.221	0.520	0.462	0.511	0.754	0.892	0.823	0.598
TWL	Public	0.516	0.715	0.618	0.715	0.819	0.826	0.825	0.719
ZAL	Public	0.227	0.599	0.456	0.544	0.788	0.878	0.832	0.618
ZACL	Public	0.551	0.803	0.684	0.827	0.840	0.830	0.831	0.767
ZGL	Public	0.598	0.814	0.578	0.808	0.866	0.864	0.943	0.782
RC&F	Public	0.220	0.530	0.400	0.480	0.800	**0.810**	0.905	0.592
FDI Firm		0.403	0.451	0.482	0.607	0.700	0.786	0.831	0.609
Private Firm		0.334	0.371	0.430	0.441	0.696	0.851	0.862	0.569
Public Firm		0.455	0.531	0.572	0.702	0.802	0.820	0.845	0.675
Average		0.397	0.451	0.495	0.583	0.733	0.819	0.846	0.618

To find out the effect of a paradigm shift on the regulatory policies, we need to analyze the environmental efficiency trend of each group. Figure 3 shows the trend of environmental efficiency of Indian agriculture and its related firms (FDI, private, and public) during 2013–2019. The three groups started from the lowest efficiency value in 2013 and achieved the highest average efficiency in 2019. This steady increasing trend strongly supports the Porter hypothesis since regulation leads to increased performance throughout all the FDI, private, and public firms. With regard to respective group performance, it is notable that the private firms group shows very rapidly increasing environmental efficiency. This group showed lower than FDI and public in 2013; however, it finally surpassed them after 2018. The reason could be due to the demonetization of the banknote in India in 2016. Banknotes account for 86% of the country's circulating cash, but their effects were only felt for its fiscal year in 2016. Transactions in the Indian agricultural sector (especially private firms) are heavily dependent on liquidity, which, in turn, could have impacted the private firm group's performance in terms of environmental efficiency in 2016

[38,39]. Since the private firms are the most sensitive to the financial measures, this result suggests that a more customized financial support for environmentally friendly agricultural firms will result in stronger performance on GHG emission abatement. Furthermore, in terms of GHG measurement guidelines and a national benchmarking system, Indian firms still face a lack of uniformity and lack of managerial innovation, although they recognize the benefits of sustainable firms' practices, implying financial incentives by the government as one of the best market-oriented measures [36].

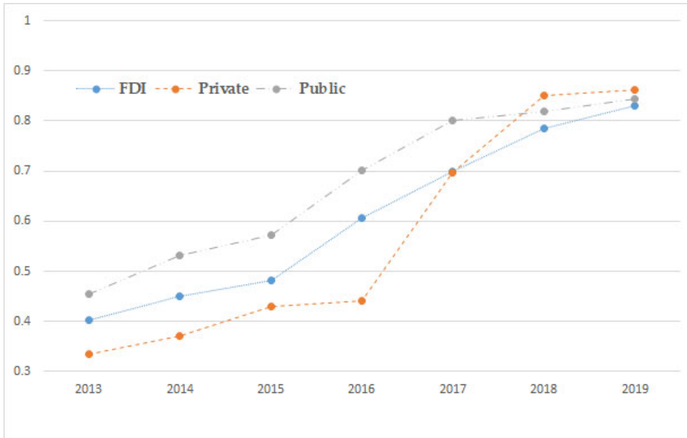

Figure 3. Trends of agriculture and its related firm's environmental efficiency.

4.2. Descriptive Statistics for Factors Affecting Inefficiency in Indian Agricultural Firms

Based on the result of environmental efficiency, we may find out the answer to the research question: What are the main sources of inefficiency, and is there a way to improve the efficiency of the agricultural and its related sector in India? To address this issue, we conducted Tobit regression for the determinants of efficiency (or sources of inefficiency) measures as the second stage of this study. As discussed in Section 2, we selected the eight explanatory variables: land, livestock, fertilizers, various agriculture cultivation, urbanization rate, climate change—average rainfall, economics openness—export, and credit, as determinants of efficiency (or source of inefficiency) measures in agriculture and its related sectors. Due to the lack of firm data, we could not select all 56 firms; instead, we chose 30 out of 56 firms to deploy Tobit regression in the second stage of our study. We have collected all the explanatory variables from the annual report of 30 firms from agriculture and its related sectors for 2019. For urbanization rate data, we refer to the data from Census of India, Govt. of India and Reserve Bank of India, Handbook of Statistics on Indian States [40,41]. We considered the state-level Population in Urban Area as the urbanization rate data as there was insufficient data from the firms. Then, we segmented our selected firms into state-level and extracted the data, as each firm is located in different states. Likewise, due to the limited data, we were unable to extract the average rainfall data from the firm; instead, we collected the data from the Indian Meteorological department, Ministry of Earth Science, New Delhi, at state level [42]. For the dependent data, we chose the efficiency scores from the first stage. Descriptive statistics for these determining factors are shown in Table 5.

Table 5. Descriptive statistics for determining factors explaining inefficiency in Agricultural firms.

Explanatory Variables (Unit)	Mean	Std. Deviation	Maximum	Minimum
Land (Million rupees)	0.75	0.70	4.90	0.20
Livestock (Tons)	11,052.00	6502.46	30,000.00	0.00
Fertilizers (Kg. Per Hectare)	100.83	27.73	143.00	11.00
Agricultural cultivation (Mil. hectares)	22.13	6.96	32.23	3.24
Urbanization rate (Percentage)	30.00	8.746	40.620	6.800
Average rainfall (Millimeter)	1226.60	833.56	4321.00	108.00
Economics openness- export (Million rupees)	286.93	298.35	1029.19	1.63
Credit access (Million rupees)	5171.53	1522.62	11,621.76	1000.84

4.2.1. Results of Tobit Regression

For the determinants to enhance environmental efficiency, Table 6 shows the results of the Tobit model with the comparative results of the OLS to determine whether they have a significant difference with each other. Indeed, as shown in Table 6, the OLS estimates show a different pattern from those of Tobit estimates in terms of the significance level. As mentioned in Section 2, the Tobit model has the advantage of being used to avoid bias and inconsistencies when estimating unknown parameters, making a more appropriate choice for evaluating the determinants of environmental efficiency [43]. Besides this, the results of the OLS model contradict the Tobit model in many respects. In the Tobit model, the use of fertilizer has a strong negative effect on environmental efficiency, while OLS does not have any statistical significance regarding that at all, contradictorily against the fact that most agricultural firms heavily depend on fertilizers. Therefore, the OLS approach results in not only theoretical bias on the limited dependent variable of environmental efficiency but the practically unacceptable implications [44]. Therefore, we concluded that Tobit regression is a superior methodology in this study and offers more appropriate implications in theoretical as well as practical perspectives.

According to the Tobit regression result, among other variables, two variables (fertilizer and agricultural cultivation) show a negative influence on environmental efficiency, at the significance level of 99%. Fertilizer use appears to have the highest negative impact on India's environmental efficiency. A 1% increase in fertilizer use will reduce India's environmental efficiency by 3.350%. Moreover, some experts have also argued that the overuse and imbalanced use of fertilizers in some parts of India has caused environmental degradation problems in India [45–47]. Our empirical result certainly supports this view of the fertilizer issues on the environment of India. In addition, Indian environmental efficiency is negatively affected by various rice cultivation every year. This means that if there is more agricultural cultivation in India, GHG emissions are likely to increase and affect environmental efficiency, leading to environmental degradation. However, apart from rice cultivation, the intensity of GHG emissions from other crops has remained reasonably low because these crops are grown in rainfed conditions in India. Furthermore, to reduce GHG emissions from rice fields, the government has proposed additional sustainable agriculture actions [47]. In contrast to two negative variables, land, economics openness—export, and credit access positively impact Indian environmental efficiency significantly. In addition, export has a positive impact on Indian environmental efficiency, which means that larger exports will not harm Indian environmental efficiency, as India is one of the major exporters of agriculture and its related sector. Finally, credit access appears to have positively impacted Indian environmental efficiency, which means that Indian firms need more sources of finance to improve the environmental efficiency of agriculture and its related sectors through advanced equipment or techniques. On the other hand, livestock, urbanization rate, and average rainfall did not show statistical significance on environmental efficiency.

Table 6. Comparison of empirical results of Tobit and OLS models.

Dependent Variable = Efficiency Scores from the First Stage of the DEA Application					
		OLS Model		Tobit Model	
Explanatory Variables	**Unit**	**Coefficient**	**t-Statistics**	**Coefficient**	**t-Statistics**
Land	Million rupees	0.742	5.690 ***	0.765	3.130 ***
Livestock	Tons	−1.575	−2.830 ***	−1.850	−1.310
Fertilizer	Kg. Per Hectare	−2.836	−0.595	−3.350	−2.905 ***
Agricultural cultivation	Million hectares	−0.020	−5.450 ***	−0.010	−5.030 ***
Urbanization rate	Percentage	−0.030	−1.740 *	−0.027	−1.090
Average rainfall	Millimeter	0.152	1.772 *	0.051	1.122
Economics openness—export	Million rupees	0.015	4.720 ***	0.013	2.160 **
Credit access	Million rupees	2.579	2.560 **	2.710	2.150 **
Industry fixed effects		Yes		Yes	
FDI/Private/Public fixed effects		Yes		Yes	
Year fixed effects		Yes		Yes	
Year of observation		2019		2019	

Note: ***, ** and * indicates the significance level of 1%, 5% and 10% respectively.

5. Conclusions

This study analyzes the environmental efficiency of agriculture and its related firms in India for seven consecutive years (2013–2019). We used the SBM-DEA method in the first stage of our study to determine the environmental efficiency of sample firms. In the second stage of this study, we used the Tobit model to find out the determinants of efficiency (or sources of inefficiency).

Empirical results and implications are summarized as follows. First, the non-radial SBM-DEA approach showed huge potential with 32.3% on average for the Indian firms of FDI, private, and public groups to improve their performance if they move toward the production frontier. This indicates that Indian firms still have to improve the agricultural sector's performance to make it sustainable. Second, for the effect of a paradigm shift on the environment-friendly policies in recent years, our results showed an improvement in environmental efficiency in India at the firm level during the research period. Nonetheless, the trend shows a very smooth and marginal improvement trend among the agricultural firms regardless of different classification among the three groups, FDI, private, and public firms. This suggests that the regulation should be much stronger in terms of the use of agricultural inputs such as energy (fertilizers) in India, especially on the FDI firms with precisely performance-oriented customized financial measures, as agricultural sectors are the primary sectors in the Indian economy. Third, to find out the main sources of inefficiency and a way to improve the efficiency of the agricultural and its related sector in India, we deployed a Tobit regression model in the second stage of this study. We found that two variables, fertilizer and agricultural cultivation of rice, negatively impact India's environmental efficiency, suggesting that fertilizer use and cultivation of agriculture should be minimized to improve the efficiency of agriculture and its related sectors in India. Here, we suggest that the Indian government provide designated loans or grants to agricultural firms in the form of soft loans (or credit access) for the purchase of high-quality fertilizers and to adopt energy-saving equipment/technology to minimize the use of chemical fertilizers. As shown in the Tobit regression result, the credit access shows the highest positive relationship to India's environmental efficiency and vice versa for fertilizer use.

This research shed light on the optimal path of the regulatory as well as the promotional policies for an environmentally friendly agriculture industry in developing countries. In most developing countries, the agriculture industry may be the largest or a major engine of economic development. Thus, more precise, appropriate policies to enhance green growth are feasible and sustainable, with a strong lead through the regulation and promotion policies in more performance-oriented ways.

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