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Technical Efficiency of Chemical Fertilizers Use and Agricultural Yield: Evidence from India

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ABSTRACT

The agriculture sector is a significant contributor to food security and employment in India, where sustainable yield in agriculture is a prime concern. The heavy and improper use of chemical fertilizers persists in technically inefficient agricultural production. This study attempts to evaluate the technical inefficiency of chemical fertilizers' use and measure the potential minimization of fertilizer input without compromising the agricultural yield level. The study uses secondary data from 2006 to 2015 from 28 Indian states and empirically analyses the efficiency of chemical fertilizers use and their impact on agricultural yield by incorporating slack-based Data Envelopment Analysis (DEA). Three chemical fertilizers, namely; Nitrogen (N), Phosphorus (P), Potassium (K), and gross irrigated land area, have been taken as input variables, and States Total Food-grain (STFG) has been taken as the output variable. The conventional slack-based DEA procedure may have biased efficiency estimates, therefore in the second step, the Double Bootstrap DEA procedure is followed to correct the biasness of efficiency scores that further checks the moderating relation between efficiency scores and agricultural credit using #algorithm1 and #algorithm2 of Simar and Wilson (2007). Findings indicate that fertilizer K has a higher possibility to decrease, followed by P and N. Evidence from double bootstrap establishes a positive relationship between agricultural credit and yield. Hence, farm-level policies, budgetary implications of agricultural credit, and awareness about the proper use of fertilizers will help reduce chemical fertilizer intensiveness in production and enhance the farmers' income through input saving strategy.

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1. Introduction

It is expected that the global food demand in 2050 will touch 9.1 billion, which is double comparatively the current production level of food grains. However, global agricultural production only increased by 28% from 1985 to 2005 (Ray et al., 2012). This increasing demand requires necessary steps that focus on agricultural productivity with sustainability. Agriculture is a purely competitive market where crop production and resource input utilization (e.g., Fertilizers use optimization) both have either a diverse or uniform competition scenario (Debertin, 2012). There is a synergistic effect of an ample amount of fertilizer phosphate (P), which increases the productivity of potash, and a synergistic effect of more than one fertilizer sync for better soil fertility. The report by Syers et al. (2008) concludes that the efficiency of the fertilizer P is often high by using the adequate or balanced method of utilization. The improper use of chemical fertilizers adversely affects soil health, crop yield, and the ecosystem in the long term (Patra et al., 2016).

In the academic domain, sizable literature is available on chemical fertilizer uses and their impact on agricultural production. Duflo et al. (2009) did a real-world experiment in Kenya on small farmers' fertilizer adoption behavior. They raised the question, of whether the farmers who are using fertilizers effectively benefit in terms of profit return or not. For this, they demonstrated a series of plot experiments in small farmlands and found that in controlled plots, fertilizer usage appeared profitable with the condition of appropriate quantity use. A literature review-based study carried out by Branca et al. (2011) stated that improvement in cropland management would further increase crop productivity.

Similarly, Shah and Wu (2019) suggested that the agricultural production system can be enhanced by developing combined multifaceted efforts, reducing pesticides, and chemical fertilizers, and improvement in crop yield efficiency to help in agricultural sustainability. Thibbotuwawa and Mugera (2014) studied the fertilizer use efficiency of rice farms in Sri Lanka by applying a non-parametric slack-based DEA analysis for the years 2007 to 2010. Their study revealed that fertilizer use has relatively lower inefficiency and can decrease by 13% without compromising the rice yield.

Despite the above literature, a minimal number of studies have been carried out in India. However, such studies remain narrow in focus dealing only with a single state, district, and regional level. Kumar and Kapoor (2007) examined the intensiveness of buying agricultural production inputs by Indian farmers. The farmers lack precision on how to use chemical fertilizers. Buying these fertilizers and agrochemicals without routine and balanced fertilizers positively affects farm income and increases crop yield. Prasad R. (2009) investigated that the inception of the green revolution in India has raised higher food-grain production by using intensive chemical fertilizers.

The fertilizer consumption in India increased by 322 times compared to only five times an increase in cereals production from 1950-51 to 2007-08. Pathak et al. (2003) reviewed the use of chemical fertilizers by using published field experiment data in

India. This review has demonstrated that fertilization has been mostly focused on nutrient support for wheat plants. Jaga and Patel (2012) found that fertilizer consumption in India is highly skewed with inter-state and inter-regional consumption levels in the agricultural field. Their results show that non-price factors such as seed variety and irrigation are comparatively important for fertilizer consumption.

Tan et al. (2015) examined state-wise Total Factor Productivity (TFP) of crops from 2000 to 2010 period in India by incorporating Malmquist Data Envelopment Analysis (DEA). The empirical results reveal the possibility of production enhancement with existing technologies and their efficient utilization. Patra et al. (2016) studied the implication of chemical fertilizers and their intensification for the growth of agricultural production in the Hooghly district of West Bengal, India. They applied multivariable regression and correlation methods to analyze the growth of agricultural production and crop yield. Their study revealed no strong correlation between intensive chemical fertilizer usage and agricultural yield, and fluctuations occurred in productivity due to the improper use of N. P. K. fertilizers.

Over the past century, there has been a dramatic increase in chemical fertilizer consumption in developing countries. After the green revolution, it appeared globally a trend to stress a different level of fertilizers used to increase agricultural productivity. The immediate effect of the green revolution in many developing countries motivated government budgetary policy to subsidize fertilizers and intensified chemical fertilizer usage. However, the overall effective return to the farmers appeared low for many countries. Further, many developing nations reduced fertilizer subsidies due to their inefficient use, fiscal constraints, and corruption in subsidy plans. Mainly three chemical fertilizers- Nitrogen (N), Phosphorus (P), and Potassium (K) are intensively in use, and subsidizing these fertilizers has been one of the most challenging policy debates in developing countries. In Asia, India, and China have stagnated in crop yield in pre-21st century periods, while fertilizer use in India has increased from 2.65 million tonnes in 1971-72 to 28.12 million tonnes in 2010-11.

The undiscriminating exploitation of natural resources in cultivated areas has raised concern about the sustainability of agricultural production in India. The Indian farming system has been characterized as fragmented small landholdings by many farmers, and it depends on rain for irrigation. Soil and climatic conditions are vital in interpreting the different agricultural practices and their nexus with crop yield and mitigation. The productivity of agricultural land is defined as the ability of soil to produce a certain amount of crops, which encompasses soil fertility and other nutrients affecting crop growth (Karlen, 2005). India ranked as the second-largest chemical fertilizer consumption-demanding country after China. The agricultural production problems in India are hugely significant and can be seen as increasing input costs in prevailing years, low yield, decreasing land sizes, and inefficiency in production. In addition, Indian agriculture practice has been drastically increasing the use of chemical fertilizers s and increasing production costs in the last few decades (Yadava and Komaraiah, 2020).

In economics, production theories may have a set of input variables for the desired output level. Some of these variables might have no direct effect on output in terms of technical unit changes, but they affect profit. The big question emerges in agricultural production in which, with given input constraints, how much output can be increased. The multi-factor model of production theory states that different inputs are used to produce a single output. The growth of the plants depends upon nutrient inputs (fertilizers). Von Liebig has given this concept, and it is known as the 'Law of Minimum', which states that limiting the nutrient level to plants responsible for growth is constrained. The farmers are assumed to be rational, and their motive is to increase profit by agricultural production. The evidence reviewed here suggests a pertinent role for chemical fertilizers in agricultural yield. It is of interest to know whether farmers are rational for minimizing agricultural input for optimum output.

The TFP can be measured through single factors of production either in terms of labor productivity (mainly for cost and revenue optimization) or in terms of land productivity which accounts for output per hectare (See FAO report, 2018). This paper deals with the second orientation of agricultural yield (output per hectare) that access to land productivity using input ingredients directly affects the agricultural yield. The decision of farmers regarding input usage (mainly chemical fertilizers) in agricultural production might differ, and this difference creates a comparative efficiency choice for analysis. Considering the optimization of agricultural production by farmers at the state level, this study provides an overview of the efficiency analysis of agricultural yield (production per ha) and input usage by Indian states. States are considered decision-makers or decision-making units (DMUs) that want to optimize their production or produce efficiently. A non-parametric slack-based Data Envelopment Analysis (DEA) is used to measure the efficiency of agricultural yield. The conventional DEA procedure may lead to biased efficiency estimates. Therefore to tackle this issue, we applied the Double Bootstrap DEA method to correct the biasness and examined agricultural credit relation with estimated agricultural yield. The agriculture credit is considered an exogenous factor or determinant that affects the agricultural yield level of DMUs.

The remainder of the paper is organized as follows: the second text section contains the study's objectives, followed by the methodology, data, and variables in the third section. In the fourth section, results are discussed. The conclusion and various policy suggestions are presented in the fifth section of this paper.

2. Objectives of the Study

The main objectives of this paper are:

(i) To evaluate the efficiency of chemical fertilizer use and its impact on agricultural yield in India.

(ii) To find out, if is there any amount of chemical fertilizer deduction possible for efficient agricultural yield in India.

(iii) To find out the robust estimates of efficiency level and the relationship between agricultural credit and yield.

3. Methodology

The methodology of this paper has been divided into three approaches- the first approach follows the slack-based DEA analysis for efficiency measurement. The second method applies a correlation analysis between the input and output variables of the DEA model. In the final step, we estimated the biasness of efficiency estimates and the relation between agricultural credit and yield through double bootstrap DEA#algorithm1 and #algorithm2 developed by Simar and Wilson (2007).

Production technology is defined as a method for transforming inputs into outputs. The efficiency measurement in production technology provides a relative estimate of outputs by input utilization in the production system. The decision-maker or decision manager who controls the production through their decisions can be an individual, a firm, an industry, government institutions, or the government itself (O'Donnell, 2018). The efficiency assessment in production theory mainly has two branches, the first is parametric, and the second is the non-parametric efficiency measurement technique. The well-known parametric tool is Stochastic Frontier Analysis (SFA) which assumes a production function (e.g., Cobb Douglas production function) criterion to estimate the efficiency scores of a decision-making unit (DMU[1]). The parametric tools have functional limitations related to homogeneity, multiplicative input set, and linearity, which might not be a real-world condition that ultimately affects the result (Yadava and Neog, 2019).

Despite this parametric method, the non-parametric Data Envelopment Analysis (DEA) is a widely accepted methodology for efficiency measures. The DEA does not require any functional form of production technology and provides information about production targets. The pioneering work related to efficiency measurement emerged with Farrell in 1957. Later in 1978, Charnes, Cooper, and Rhodes (CCR) developed the Constant Returns to Scale (CRS) based DEA model for efficiency measurement. In 1984, Banker, Charnes, and Cooper (BCC) developed a Variable Returns to Scale (VRS) based DEA model. Both models have limitations in that they only provide a proportionate change effect of inputs on outputs, which is generally called a radial measurement of efficiency in DEA literature. To overcome this problem, Tone (2001) developed a non-radial model of DEA, known as the Slack-based DEA model. The slacks are generally deducted in inputs without compromising the outputs, and this is also known as the input-oriented (IO) slack DEA model.

The non-radial movement of input slacks gives a specific input reduction projection for an operated production unit under CRS or VRS frontier. The frontier is the line at which all efficient DMUs perform. The critical difference between radial and non-radial movements of inputs used in a CRS production frontier can be understood in Figure 1, where two inputs (x1, x2) are used in production. States are considered DMUs for this paper, so states 1, 2, and 3 are depicted in which state 1 and state 2 are working efficiently (DMUs with best practices) and are on the frontier. State 3 is an inefficient state working below the frontier. Moreover, state 3 has two options to optimize given

1. This paper considers the Indian states as DMU for assessment of efficiency scores.

inputs: either decrease both inputs (x1, x2), which generally means taking a radial movement to reach the frontier, or decrease input x1 or x2 non-radially reach the CRS frontier.

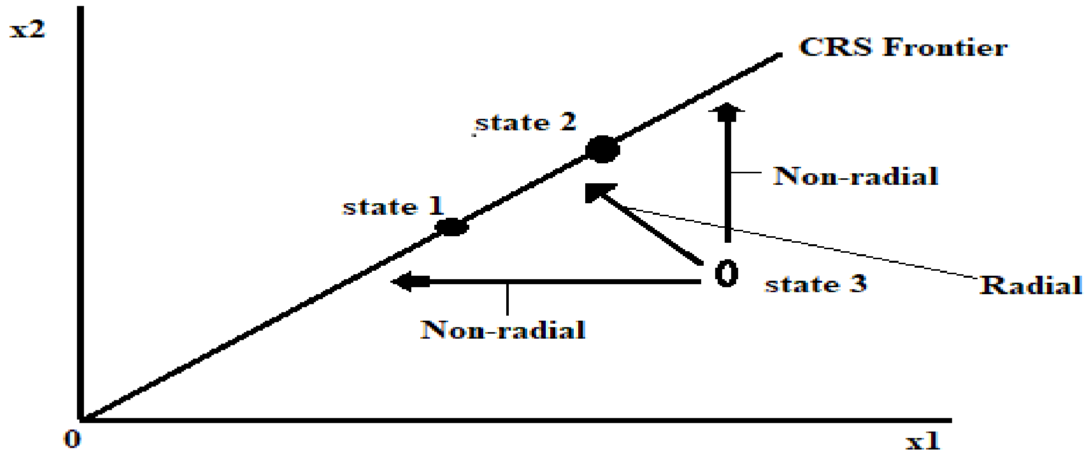

Figure 1. Radial and Non-Radial Movements under CRS Frontier
Source: Research findings.

3.1 Input-Oriented Slack-Based DEA Model

The slack-based DEA model is the second stage model of basic DEA[1].

Let ρ, a scalar represents slack based inefficiency. For the given input and output weights, λ is a $n \times 1$ vector and s^- and s^+ are input-output slack variables respectively. $X = \{x_{jj}\}$ represents the input set, where $i = (1, \dots\dots\dots, I)$ of the DMU (state) j and $Y = (y_{rj})$ represents r^{th} output of the DMU j, where $r = (1, \dots\dots\dots, R)$, the zero subscript shows that the state (DMU) is being evaluated. The slack-based DEA model is as follows:

$$Min_{\lambda, s^-, s^+} \rho = \frac{\left[1 - \dfrac{1}{I}\displaystyle\sum_{i=1}^{I} \frac{s_{ijo}^{\ -}}{x_{ijo}^{\ +}}\right]}{\left[1 - \dfrac{1}{R}\displaystyle\sum_{r=1}^{R} \frac{s_{rjo}^{\ +}}{y_{rjo}^{\ +}}\right]}$$

Subject to $$x_0 = \lambda X + s^-$$

$$y_0 = \lambda Y + s^+$$

$$\lambda, s^+, s^- \geq 0$$

Source: Cooper et al. (2007).

1. See, basic DEA models by Charnes et al. (1978); Banker et al. (1984)

The efficiency score of the input-oriented DEA model varies from 0 to 1. The value of efficiency equals 1, which means that a particular DMU is efficient. The slacks associated with the input variables are called input slacks (excess input), and the slacks linked with output variables are called output slacks (output shortfall). The DMU with 0 slack represents technical efficiency, and if a DMU has an efficiency score of 1 and has some positive slack value, meaning that DMU is weakly efficient (weak efficiency).

The conventional DEA procedure may have biased estimates. Therefore we have followed a semi-parametric two-step procedure or double bootstrap DEA procedure developed by Simar and Wilson (2007) to overcome from biasness issue. The double bootstrap method accounts for estimating efficiency scores followed by an econometric analysis into two steps. In the first step (#algorithm1) it calculates the efficiency score and considers them as the dependent variable and does a truncated regression through Data Generating Process (DGP) over theoretically considered factor variables (which can affect the efficiency score) as independent variables. In the second step (#algorithm2), it calculates the biasness in efficiency scores. It again does a truncated regression through DGP considering the bias-corrected efficiency score as dependent and the factor variables as an independent or explanatory factor (See Badunenko & Mozharovskyi, 2016). The two econometric models of double bootstrap DEA are as follows;

Model: 1 (#algorithm1 of Simar and Wilson 2007)

$$Efficiency_{i(conv)} = \text{f}(\text{Agri\_cred}_i, \beta)$$

Model: 2 (#algorithm2 of Simar and Wilson 2007)

$$Efficiency_{i(BC)} = \text{f}(\text{Agri\_cred}_i, \gamma)$$

where $Efficiency_{i(conv)}$ is estimated conventional slack-based DEA efficiency vector, and $Efficiency_{i(BC)}$ is the bias corrected efficiency score vector. ‘Agri_cred’ is a vector of agricultural credit. β and γ are associated parameter vectors to be estimated.

3.2 Data and Variables

This paper uses data for the period from 2006 to 2015 of 28 Indian states[1]. A total of 10 years of data have been taken to cover structural changes in the agriculture sector of India. Most of the compiled data was obtained from the Agricultural Statistics of India, Handbook of Statistics on Indian Economy- RBI, and the States of India-Centre for Monitoring Indian Economy (CMIE). Data of all four input variables, three fertilizers (N, P, K), and state-wise gross irrigated area (land use), along with one output variable, state-wise total food grains (STFG), have been normalized by the mean normalization method. Extrapolation[2] has been done for the data of fertilizer N for states; Arunachal Pradesh, Jammu and Kashmir, Meghalaya, and Mizoram. For the double bootstrap procedure, we have taken the log value of agricultural credit.

1. Data of the state Telangana have merged with Andhra Pradesh from 2011-12 to 2014-15 period.
2. By taking 5-year trend in the data.

4. Results and Discussion

This paper applies an input-oriented slack-based DEA model under the VRS criterion to measure the efficiency scores and input slacks. The result shows that 10 states are efficient and 18 states are inefficient (See Table 4 and Figure 2 in the Appendix). A summary of the model is presented in Table 1, which shows the average technical efficiency score of the agricultural yield of Indian states is 63.05% by using chemical fertilizers and irrigated land area as input variables. The corresponding Bias Corrected (BC) average efficiency score is 58.9%. The states' efficiency scores also reveal that, on average, the input could be decreased by 41% (as per BC scores) without compromising the output level (agricultural yield). The slack values of different input variables highlight that fertilizer K could be deducted extensively compared to fertilizer P and N. On average, fertilizer K has higher slack values comparatively P and N. The land input variable has a very moderate slack.

The efficient states with efficiency scores equal to 1, such as; Uttar Pradesh, Punjab, and Rajasthan. We can observe that these states have large irrigated land areas with fertile river basin facilities. These states are also known for high food grain production in India in absolute terms of productivity. The technological advancements of farmers in Punjab and western Uttar Pradesh can be seen as efficient resource utilization. The north Indian states like- Arunachal Pradesh, Assam, Nagaland, and Mizoram are highly motivated towards organic farming practices and less driven by chemical fertilizers. This optimized chemical fertilizer use can be observed from the slack values of these states. The observed slacks for inputs are zero for all these states indicating efficient use of inputs. Interestingly, there are high slack values for all inefficient states, and it concludes that improper or intensive use of inputs leads to inefficient production.

Table 1. Summary of Input-oriented Slack-based DEA (VRS) Model

	Efficiency score	Efficiency (BC)	Slack N	Slack P	Slack K	Slack land
Average	0.631	0.589	0.519	0.543	0.786	0.035
Max	1	0.985	6.306	5.301	8.386	0.56
Min	0.090	0.081	0	0	0	0
St. Dev.	0.315	0.306	1.1972	1.0077	1.6325	0.109

Source: Research findings.

Table 2. Correlation Matrix of Input and Output Variables

	N	P	K	land	STFG
N	1	0.969	0.869	0.137	0.161
P	0.969	1	0.909	0.156	0.184
K	0.869	0.909	1	-0.107	-0.108
land	0.137	0.156	-0.107	1	0.967
STFG	0.1611297	0.1841866	-0.108609	0.9676367	1

Source: Research findings.

The correlation matrix (See Table 2) gives effective instruction in support of DEA results. It shows a negative correlation between fertilizer K with STFG and irrigated land, which means intensifying K decreases the irrigated land size. Also, a negative effect on agricultural yield in India can be boosted by decreasing the use of fertilizer K in the field. There is a moderate correlation being seen between fertilizer P and K with STFG. The causes behind this moderate correlation may relate to the indecorous effect of different fertilizers. The low agricultural yield is related to the imbalanced use of fertilizers and their synchronization, which can be reduced by awareness of the use of fertilizers (See GOI, 2017).

Table 3. Econometric Models Result

Model	Number of observations	Coef. & (Std.Err.)	R^2
1	28	0.0409* (0.02)	0.005
2	28	0.0672* (0.03)	0.162

Source: Research findings.
Notes: *significant at 95% confidence interval, 2000 bootstrap replicas for both models.
Model 1 indicates #algorithm1 and model 2 indicates #algorithm2 of Simar and Wilson (2007).

The Simar and Wilson (2007) double bootstrap method corrects the biasness in corresponding DEA model efficiency scores and gives an econometric test for the defined exogenous factor on the efficiency scores. We test agricultural credit as an exogenous variable that influences the agricultural yield in India. Model 1 considers conventional efficiency scores as a dependent variable, and Model 2 considers bias-corrected efficiency scores as a dependent variable. For both models, agricultural credit is considered a factor (explanatory) variable. Both models were estimated using Simar and Wilson's (2007) algorithms for 2000 bootstrap replicas. The associated r-squared for both algorithms is very low because some other factors may affect the efficiency scores. The considered framework only gives a partial relationship scenario among variables of the models. Table 3 shows that agricultural credit has a positive and significant impact on efficiency scores for both models. The results are in line with the findings of Das et al. (2009). We can see the influence of agricultural credit on efficient agricultural production. Therefore proper channelized agricultural credit with support of institutional training to the farmers and promoting soil testing for the efficient production process is highly recommended for the Indian agricultural system.

5. Conclusion

This paper investigates fertilizers use and its impact on agricultural yield in India during the period 2006 to 2015. The Indian states are considered decision-makers for the implementation of proper fertilizer usage in agricultural farms. The main novelty of the paper is that it is the first kind of assessment for efficiency measurement by using chemical fertilizers and provides slacks deduction measures of fertilizers for 28 Indian states separately. This study aims to estimate the possible biasness in the conventional slack-based DEA method and find out the relation between agricultural credit and agricultural efficiency following the double bootstrap DEA procedure developed by Simar and Wilson (2007). The input-oriented DEA efficiency score reveals that the states have average technical efficiency of about 59% (bias-corrected efficiency) for agricultural yield by using four inputs (chemical fertilizers N, P, K, and irrigated land area) in the production process. The average efficiency score of the states is revealing that the input use can be decreased by approx. 41% without any deduction in agriculture yield.

The slack value reveals that the states are using more chemical fertilizers. The empirical results show that there should be an intensive decrease in chemical fertilizer K, followed by fertilizers P and N. The double bootstrap procedure shows, on average, a 4% variation in efficiency scores due to the biasness of the conventional slack-based DEA method. The estimate of econometric models from #algorithm1 and #algorithm2 establishes a positive relationship between agricultural credit and yield level. These findings are relevant to both practitioners and policy-makers and suggest that agricultural credit's role should be efficient and sustainable for agricultural practice in India. Institutional training for the farmers, promotion of soil testing for efficient production, a more comprehensive information system for input utilization, and institutional guidance about proper combination input use (especially chemical fertilizers) would help efficient farming practices in India.

Limitations of the study

This study excluded some input variables such as irrigation and pesticides because these inputs widely swerve across Indian states, and continuous data for all states are not available.

References

Badunenko, O., & Mozharovskyi, P. (2016). Nonparametric Frontier Analysis Using Stata. *Stata Journal*, *16*(3), 550-589.

Banker, A. R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, *30*(9), 1078-1092.

Branca, G., Mccarthy, N., Lipper, L., & Jolejole, M. C. (2011). Climate Smart Agriculture: A Synthesis of Empirical Evidence of Food Security and Mitigation Benefits from Improved Cropland Management. *FAO, Working Paper*, *1*, 1-27.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the Efficiency of Decision-Making Units. *European Journal of Operational Research*, *2*, 429-444.

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). Data envelopment Analysis: A Comprehensive Text With Models, Applications, References and DEA-Solver Software. In *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software* (2^{nd} Ed.). Berlin: Springer.

Das, A., Senapati, M., & John, J. (2009). Impact of Agricultural Credit on Agriculture Production: An Empirical Analysis in India. *Reserve Bank of India Occasional Papers*, *30*(2), 1118-1124.

Debertin, D. L. (2012). *Agricultural Production Economics*. Lexington: Macmillan Publishing Company.

Duflo, E., Kremer, M., & Robinson, J. (2009). Nudging Farmers To Use Fertilizer: Theory And Experimental Evidence From Kenya. *American Economic Review*, *101*(6), 2350-2390.

Cachia, F. (2018). *Guidelines for the Measurement Of Productivity And Efficiency In Agriculture*. Retrieved from 10.13140/RG.2.2.31566.72006

Dalwai, A. (2017). *Report of the Committee on Doubling Farmers' Income*. Delhi: Government of India (GOI).

Jaga, P. K., & Patel, Y. (2012). An Overview of Fertilizers Consumption in India : Determinants and Outlook for 2020-A Review. *International Journal of Scientific Engineering and Technology*, *1*(6), 285-291.

Karlen, D. L. (2005). *Productivity*. New York: Elsevier.

Kumar, N., & Kapoor, S. (2017). Extensiveness of Farmers' Buying Process of Agri-Inputs in India: Implications for Marketing. *Journal of Agribusiness in Developing and Emerging Economies*, *7*(1), 35-51.

Pathak, H., Aggarwal, P. K., Roetter, R., Kalra, N., Bandyopadhaya, S. K., Prasad, S., & Van Keulen, H. (2003). Modeling the Quantitative Evaluation of Soil Nutrient Supply, Nutrient Use Efficiency, and Fertilizer Requirements of Wheat in India. *Nutrient Cycling in Agroecosystems*, *65*(2), 105-113.

Patra, S., Mishra, P., Mahapatra, S. C., & Mithun, S. K. (2016). Modeling Impacts of Chemical Fertilizer on Agricultural Production: A Case Study on Hooghly District, West Bengal, India. *Modeling Earth Systems and Environment*, *2*(4), 1-11.

Prasad, R. (2009). Efficient Fertilizer Use: The Key To Food Security And Better Environment Review/Synthesis Efficient Fertilizer Use: The Key To Food Security And Better Environment. *Journal of Tropical Agriculture*, *47*(January), 1-17.

Ray, D. K., Ramankutty, N., Mueller, N. D., West, P. C., & Foley, J. A. (2012). Recent Patterns of Crop Yield Growth and Stagnation. *Nature Communications*, *3*, 1293-1297.

Shah, F., & Wu, W. (2019). Soil and Crop Management Strategies to Ensure Higher Crop Productivity within Sustainable Environments. *Sustainability*, *11*(5), 1-19.

Simar, L., & Wilson, P. W. (2007). Estimation and Inference in Two-Stage, Semi-Parametric Models of Production Processes. *Journal of Econometrics*, *136*(1), 31-64.

Syers, J. K., Johnston, A. E., & Curtin, D. (2008). *Efficiency of Soil and Fertilizer Phosphorus Use: Reconciling Changing Concepts of Soil Phosphorus Behaviour with Agronomic Information*. Rome: Food and Agricultural Organization of the United Nations.

Tan, K. G., Rao, K., & Rajan, R. (2015). How Productive Is The Agricultural Sector Across Indian States? *International Journal of Development Issues*, *14*(3), 231-248.

Thibbotuwawa, M., & Mugera, A. W. (2014). Fertilizer use Efficiency of Rice Farms in Sri Lanka: A Slack- based DEA Analysis. *11th International Conference of DEA*, April, 224–229.

Tone, K. (2001). A Slacks-Based Measure of Efficiency in Data Envelopment Analysis. *European Journal of Operational Research*, *130*, 498-509.

Yadava, A. K., & Komaraiah, J. B. (2020). Benchmarking the performance Of Organic Farming in India. *Journal of Public Affairs*, *21*(2), 1-20.

Yadava, A. K., & Neog, Y. (2019). Public Sector Performance and Efficiency Assessment of Indian States. *Global Business Review*, *23*(2), 1-15.

Appendix:

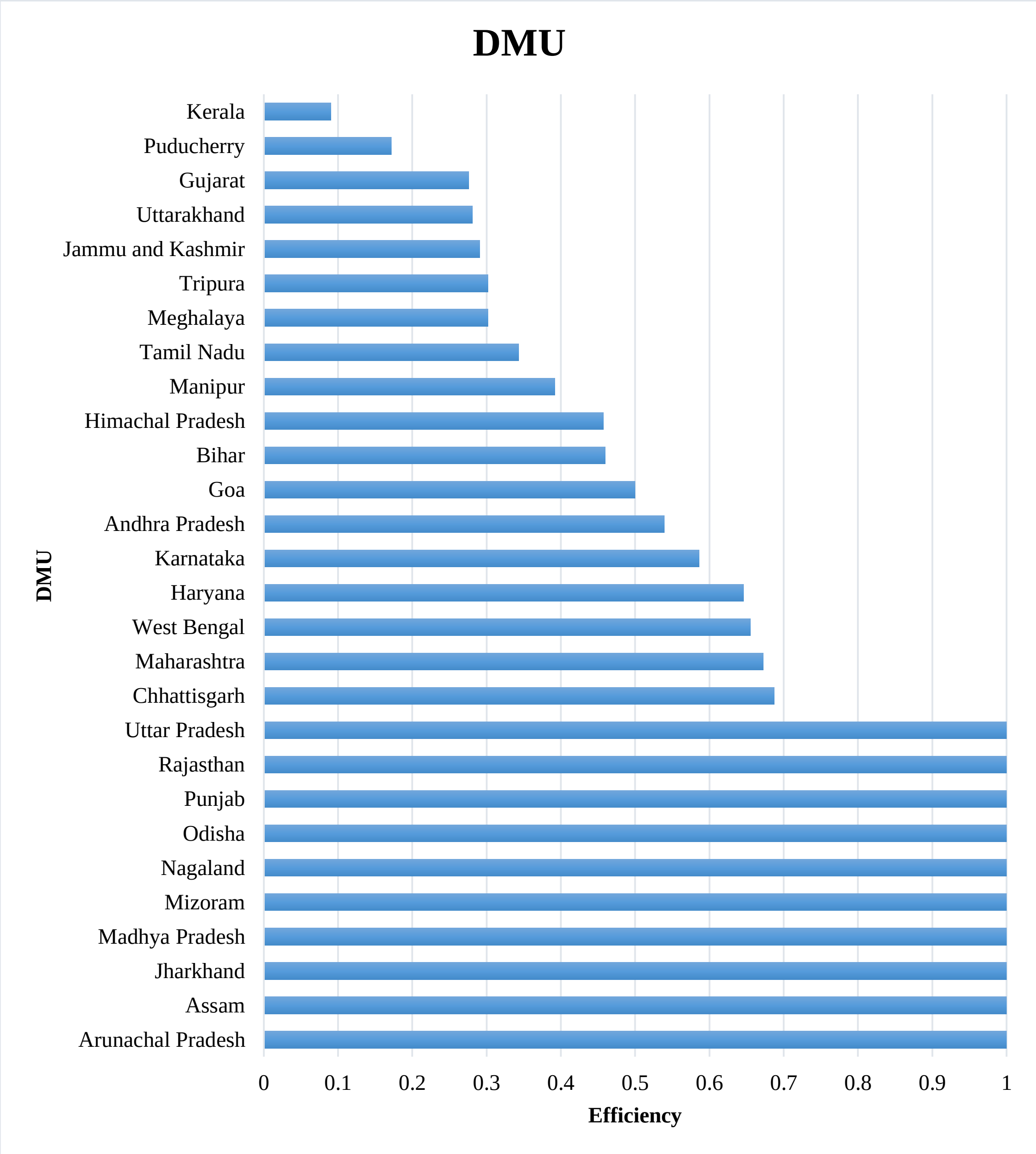

Figure 2. Efficiency Scores of the States
Source: Research findings.

Table 4. Input-oriented Slack-based DEA (VRS) Result

States	Efficiency score	Bias-corrected Efficiency scores	Slack N	Slack P	Slack K	Slack land
Andhra Pradesh	0.539	0.485	0.627	1.238	1.45	0
Arunachal Pradesh	1	0.978	0	0	0	0
Assam	1	0.985	0	0	0	0
Bihar	0.46	0.444	1.067	0.645	0.745	0
Chhattisgarh	0.687	0.598	0.095	0.339	0.385	0
Goa	0.5	0.472	0.162	0.274	0.452	0
Gujarat	0.276	0.259	0.919	0.88	0.621	0.56
Haryana	0.646	0.538	1.024	0.82	0.098	0
Himachal Pradesh	0.457	0.416	0.293	0.191	0.256	0.028
Jammu and Kashmir	0.29	0.261	0.535	0.52	0.308	0.11
Jharkhand	1	0.942	0	0	0	0
Karnataka	0.586	0.512	0.175	0.832	1.445	0
Kerala	0.09	0.081	0.427	0.57	1.615	0.116
Madhya Pradesh	1	0.932	0	0	0	0
Maharashtra	0.672	0.558	0	0.564	0.983	0
Manipur	0.391	0.357	0.464	0.186	0.182	0
Meghalaya	0.301	0.285	0.101	0.114	0.047	0.011
Mizoram	1	0.983	0	0	0	0
Nagaland	1	0.980	0	0	0	0
Odisha	1	0.956	0	0	0	0
Puducherry	0.171	0.172	6.306	5.301	8.386	0.003
Punjab	1	0.926	0	0	0	0
Rajasthan	1	0.970	0	0	0	0
Tamil Nadu	0.343	0.331	1.053	1.221	2.497	0.014
Tripura	0.301	0.291	0.272	0.388	0.416	0.01
Uttar Pradesh	1	0.964	0	0	0	0
Uttarakhand	0.28	0.261	1.016	0.447	0.344	0.133
West Bengal	0.655	0.548	0.004	0.681	1.767	0

Source: Research findings.