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Efficiency Measurement in Groundnut Production Using Data Envelopment Analysis

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ABSTRACT

Organizations aiming to be environmentally friendly while yet making a profit must prioritise efficiency. As a result of increased efficiency, a "win-win" scenario might occur. An assessment of ecoefficiency is necessary for studying and managing firms from this viewpoint. Data envelopment analysis (DEA) is examined here to assist academics and management in developing measurements for environmental efficiency. Increases in the theory and use of DEA have occurred. It hasn't seen a lot of action as an assessment instrument for environmental performance. For practitioners and researchers alike, this article discusses several DEA models and how they might be used. Figure out the capabilities and limitations of the various models by using groundnut production data from an Indian agricultural data set as an example.

Keywords: DEA, DMU, Efficiencies.

INTRODUCTION

There is a lot of interest in the quantitative approach Data Envelopment Analysis (DEA) in operations research and applications (DEA). A variety of administrative issues and research concerns have found this technique valuable, but it has not been widely used in the field of environmental management. An increasing number of methodological and application-oriented enhancements have made DEA an excellent tool for investigating a variety of management difficulties and concerns. The fact that DEA has just recently been applied to environmental challenges, along with its most recent advances, makes it an ideal candidate for further study and application. In this article, we'll look at the many uses from both a practical and a theoretical standpoint. There are many questions about how firms might improve their environmental performance, thus we show how DEA can be used to answer such concerns as well as assist management in making choices. To highlight research and application needs, the study will examine a variety of DEA-based techniques. The DEA models and extensions covered in this article are deterministic (as opposed to stochastic) models. To name a few of the more recent developments covered in this study, the use of "cross-efficiency" measures, game theoretic (pairwise comparison) approaches, and ordinal DEA techniques are just a few examples. This paper's significance to the scientific community includes a review article on DEA, methodological development, and the study objective of environmental eco-efficiency evaluation using DEA. DEA models as an ecoefficiency testing method are thoroughly evaluated in this study.

THE ENVIRONMENT AND THE DEA

DEA is known for its multifactor productivity measurements and relative efficiency. There have been a number of organisations (public and commercial) who have used the DEA method to evaluate their performance over time. External (at the industry level) and internal (at the company level) environmental problems have only received a cursory assessment by DEA. DEA may be a valuable tool in the management of environmental efficiency in organisations or institutions.
DEA estimates the relative efficacy of various units in a set using linear programming optimization as a method of quantification. A company, a facility, an industry, or any analogous grouping may be included in this list. Following Charnes, Cooper, and Rhodes' initial publication on DEA in 1978, its applications and advances have expanded.

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Modeling and studies based on DEA that take environmental variables into account already exist. Examples of macroeconomic DEA-based work that includes environmental evaluations include: energy alternatives (Criswell & Thompson, 1996); forest management (Kao et al. 1993); industrial regional development (Karkazis & Boffey, 1997); country productivity evaluations (Lovell, et al. 1995); and site location (Lovell, et al. 1995). (Ball, et al., 1994; Poit-Lepetit et al. 1997). To assess the pollution efficiency of specific facilities and/or corporations based on emission data, several studies have used DEA (see Haynes et al., 1993, 1994; Sarkis & Cordeiro, 1998; Tyteca, 1996).
While environmental concerns have been discussed extensively in economics literature, they have not been a primary emphasis in the examples given in the academic literature. This study examined or graded a variety of businesses and organisations to see where environmental performance might be improved. In these studies, the emphasis was not on business management and competition, but rather on policy. Sarkis & Cordiero are the first researchers to use DEA to assess environmental performance from a competitive standpoint (1998). From a competitive standpoint, it seems that DEA has plenty of potential for external organisational application in environmental concerns within this reasonably complete study. The company's use of DEA as a managerial tool or for environmental research is almost non-existent. An evaluation of internal environmental initiatives and projects may be done using DEA in the following section.

DEA MODELS

There are currently a lot of models to choose from. CCR and Banker et al. (1984) multifactor models will be among the models included in this study's research (BCC). These models provide researchers a chance to examine the efficiency of different units under consideration in terms of both technical and size. However, truncation issues prevent non-parametric statistical assessment or ranking of alternatives using these methods effectively. Three more variants on these ideas are presented to help overcome some of these issues. Models by Andersen & Petersen (1993), Doyle & Green (1994), and Rousseau & Semple (1995) are included in these strategies (1995a). An alternative approach by Cook et al. (1996) allows for qualitative aspects to be included into the DEA analysis process. Sark and Talluri (1999) built on Cook and colleagues' approach to increase qualitative models' discriminatory power. Deterministic DEA models based on these models give a more comprehensive set of tools for assessing an organization's eco-efficiency. In-depth comparisons of each model are provided.

Technical and Scale Efficiency DEA Models based on basic ratio-based ratios

Productivity models have typically been used to quantify the efficiency of systems. For DEA productivity models, the output-to-input ratio is typically used, based on the number of outputs generated for a certain decision-making unit (DMU). For a DMU, input and output values may be used by anybody, from individuals to governments. The simultaneous study of various inputs to numerous outputs made feasible by DEA makes it possible to use a multi-factor productivity approach. A simplified notation based on Doyle and Green is the best choice for expressing the DEA's overall efficiency assessment (1994). (1).

$$E_{ks} = \frac{\sum_{y} O_{sy} v_{ky}}{\sum_{x} I_{sx} u_{kx}} \tag{1}$$

where:
In this example,
(Eks) is the DMU k's efficiency or productivity measure;
(Osy) is the value of DMU y;
(Isx) is the value of DMU y's input;
(vky) is the weight given to DMU k for output y; and
(ukx) is the weight allocated to DMU k for input x.
CCR (1978) DEA ratio model's objective is to choose the appropriate weights associated with input and output measures in order to maximise the efficiency value of a test DMU k from an existing reference set of DMUs. Limits on the maximum efficiency are set at 1 An expression of the formulation is shown (2).

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maximize $$E_{kk} = \frac{\sum_{y} O_{ky} v_{ky}}{\sum_{x} I_{kx} u_{kx}}$$

subject to:

$$E_{ks} \leq 1 \qquad \forall \quad \text{DMUs} \quad s \tag{2}$$
$$u_{kx}, v_{ky} \geq 0$$

As shown in Charnes et al. (1978), this nonlinear programming formulation (2) is identical to formulation (3):

maximize $$E_{kk} = \sum_{y} O_{ky} v_{ky}$$

subject to:

$$E_{ks} \leq 1 \qquad \forall \quad \text{DMUs} \quad s$$

$$\sum_{x} I_{kx} u_{kx} = 1 \tag{3}$$

$$u_{kx}, v_{ky} \geq 0$$

When the efficiency ratio denominator is constrained to a value of 1, the transformation is complete. $\sum_{x} I_{kx} u_{kx} = 1$.

A value of Ekk* as close to 1 as feasible is produced by Formula (3) (the CCR formulation), which is the formula's maximum simple or technical efficiency value (this formulation has also been defined as the constant returns to scale formulation). k is the best DMU based on the weights it has received if Ekk* equals 1. There is no other DMU that outperforms DMU k at Ekk* = 1, which means that DMU k is the best DMU for this problem. There is at least one more efficient DMU than DMU k for the ideal weights provided by Ekk* if Ekk* 1 is true (3). The formula (3) is repeated s times for each DMU.

Model (4) displays the CCR formulation's envelopment side (also known as the dual).

minimize θ

subject to:

$$\sum_{s} \lambda_s I_{sx} - \theta I_{sx} \leq 0 \qquad \forall \ \text{Inputs } I$$
$$\sum_{s} \lambda_s O_{sy} - O_{ky} \geq 0 \qquad \forall \ \text{Outputs } O \tag{4}$$
$$\lambda_s \geq 0 \qquad \forall \ \text{DMUs } s$$

Assuming constant returns to scale, the CCR model is used. A model created by Banker, Charnes, and Cooper takes variable returns to scale into consideration (1984). Aids in calculating the BCC model's scalability efficiency for a group of units (which is a technically efficient unit for the variable returns to scale model). Convexity constraints have been added to this new model by restricting multiplier weight summing to one, or:

$$\sum_{s} \lambda_s = 1 \tag{5}$$

CCR and BCC models are used together to determine the DMU respondents' overall technical and scale efficiency, and whether the data shows different returns to scale for the DMU respondents.

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Cross-Efficiency Models

Basic efficiency ratings may have many "false positives," which is a serious concern. Since a false positive DMU score depends so heavily on a single input or output, it is more efficient than any other DMU (Sexton et al. [1986] define these units as mavericks). It's possible to discern between DMUs that are really efficient and DMUs that are falsely claiming to be efficient. Sexton et al. introduced the concept of cross-efficiency and the cross-efficiency matrix in their paper (CEM). The CEM analyses a DMU's efficiency by using weighting methodologies that have been optimised for other DMUs. A CEM is shown in Table 1. For each DMU k, the ideal weights are provided in the k^{th} row and s^{th} column (Eks.). When the CEM weights are based on the basic CCR model, it is feasible to derive a mean cross-efficiency measure for each DMU by averaging all of the CEM columns (defined as the simple cross-efficiency [SXEF] measure) (es). One danger of a falsely optimistic DMU score comes from devices having very low cross-efficiency values or values that are much lower than those of a previously inefficient device. Using the CCR model to calculate optimal simple efficiencies, a cross-efficiency score may not accurately represent the system's real efficiency. The creation of a CEM and the calculation of cross-efficiency may be avoided using Doyle and Green's (1994) formulation (6). This method makes it easier to come up with a clearer list of ideal weights.

minimize $$\sum_y \left(v_{ky} \sum_{s \neq k} O_{sy} \right),$$

subject to:

$$\sum_x \left(u_{kx} \sum_{s \neq k} I_{sx} \right) = 1,$$

$$\sum_y O_{ky} v_{ky} - E^*_{kk} \sum_x I_{kx} u_{kx} = 0 \qquad (6)$$

$$E_{ks} \leq 1 \qquad \forall \quad \text{DMU} \quad s \neq k$$

$$u_{kx}, v_{ky} \geq 0$$

As outlined in Doyle and Green's (6) formulation, there are two key objectives: obtaining the greatest feasible simple efficiency score for DMU k (the test unit) and finding weights that lower overall output of all DMU components. An average unit with the lowest efficiency is referred to as a "test unit k." Be a result, this paradigm has been referred to as aggressive (AXEF). the supplementary goal of maximising aggregate output of the other DMU by changing "minimum" from "minimum" to "maximum" will make the Doyle and Green formulation more benign (6). According to the second constraint set, the CCR model's ideal efficiency scores (Ekk*) are needed in (6). A two-step technique is required to establish the best weights in this cross-efficiency computation process. With just a little adjustment to the Doyle and Green algorithm, the commercial linear programming software generates more accurate results (6). By dividing the value by the n-1 average units, the goal function (n-1), which represents the total number of DMUs in the model, may be scaled up or down by a factor of six. It's possible to get the same weights (v* and u*) on a comparable scale as the CCR model using this scaling method. In preliminary testing using formulation (6), we discover that the ideal weights for offsetting the average unit size increase lower as the number of units under assessment grows bigger. The commercial LP solution package tends to truncate and round off the ideal weights as they become smaller. The efficiency of the units under examination is unaffected by the scaling of the ideal weights. For formulation (6), we propose a new metric:

minimize $$\sum_y \frac{\left[v_{ky} \sum_{s \neq k} O_{sy} \right]}{n-1} \qquad (7)$$

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In this case, n is the total number of DMUs

This algorithm may be used to rank DMU alternatives based on the mean cross-efficiency scores. It is possible to generate a maverick index score to identify false positives or mavericks (8).

$$MI_k = \frac{E^*_{kk}}{e_k} \quad (8)$$

It is the ideal CCR formulation value for the ideal test unit k CCR, and it is the cross-efficiency score for the ideal test unit (SXEF or AXEF). An index score greater than the sum of the mean of the maverick indices and a factor indicates a "false positive" in the testing process (which will be some fraction of the standard deviation of the sample). This outcome is expressed in the form of a number (9).

$$MI_{k\in E} > \overline{MI} + \rho\sigma \quad (9)$$

where

$MI_{k\in E}$ is the maverick index for a test unit *k* which is initially technically efficient,

$\overline{MI} = \frac{\sum_{j=1}^{m} MI_j}{m}$ and is the mean of the maverick indices (over the full set of DMUs *m*),

□ = $\sqrt{\frac{m\sum MI^2 - (\sum MI)^2}{m(m-1)}}$ = the standard deviation of maverick indices from the full set of DMUs *m*, and

□ = a false positivity factor.

FACULTIES THAT AFFECT THE ENVIRONMENT AS AN ENTIRE SYSTEM

Only a few research have studied the application of DEA for environmental efficiency analysis, but those that have covered a broad variety of environmental characteristics have been reviewed. EPIs or sustainability indicators may be used to determine many of the various metrics for environmental efficiency. You may choose from a wide range of indicators, ranging from an individual to a whole sector. Trying to figure out which indicators to include in a model might be a challenge. In the DEA model, the data that is picked has a significant impact.

Several sustainability features are discussed in Tyteca's (1998) article. Ecological, economic, and social indicators are the most common. Sustainability measures at the local, regional, and national levels have gotten a lot of attention (see for example Corson, 1994; UNCSD, 1995; and van Pelt, 1993). These stats are clearly more aggregated. To perform an admissible study in organisational research, there must be indicators at the corporate, plant, shop, or even individual level. Environmental reporting and research into corporate sustainability indicators, such as ISO 14000 performance standards, have made it feasible to collect data that may be used for corporate sustainability analysis. There is a wealth of information available on environmental indicators and environmental databases in Azzone and Manzini (1994), Gerde & Logdon (1999), James (1994), and Tyteca (1994). (1996).

Table 2 shows that the DEA models have a wide range of potential inputs and outputs. Data on emissions, environmental expenditures, the number of environmental programmes, and penalties are included in quantitative calculations. Environmental initiatives and statistics on reputation from different publications and organisations are examples of qualitative elements.

IMPIRICAL INVESTGATION

Ground Nut Production Analysis

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The 9 states have a significant role in **ground nuts** are considered to be the decision making units. Each state is assumed to combine two inputs to produce a single output. The distribution of efficiencies under CRS, VRS and scale efficiencies are furnished here:

Groundnut Production Efficiency

S.No.	State / UT	CRSTE	VRSTE	SCALE
1	Gujarath	0.063	0.177	0.357 drs
2	Andhra Pradesh	0.042	0.065	0.647 irs
3	Tamil Nadu	0.361	1.000	0.361drs
4	Rajasthan	0.180	0.470	0.384 drs
5	Karnataka	0.080	0.121	0.660 irs
6	Maharashtra	0.215	0.242	0.885 irs
7	Madhya Pradesh	0.288	0.400	0.720 irs
8	Uttar Pradesh	0.579	0.889	0.652 irs
9	Odisha	1.000	1.000	1.000 -

The state **Andhra Pradesh** experienced more input losses 96% as compared to other states in CRTS environment. Out of 9 states only three states experienced more than 90% input losses in CRTS and in VRTS environment only one state **Andhra Pradesh** suffered with more than 90% of input losses. Out of 9 states 50% of the states managed with increasing returns to scale environment and only 30% of the states suffered with decreasing return to scale. The only one state emerged to be efficient in CRTS is Odisha and in VRTS environment two states namely, **Odisha** and **Tamil Nadu** managed with 100% efficiency score. The following bar diagram explains the average input losses in the different environments.

Overall, the states experienced 69% of input losses in CRTs and 52% in VRTS environment respectively. Due to scale inefficiency the states experienced only 27% of input losses for this agricultural production.

Peers and Ranking of DMUs

S.No.	State /UT	Peers	Peer count	Peer Weight	Super efficiency	Rank
1	Gujarath	3, 9	0	0.901, 0.099	0.1774	7
2	Andhra Pradesh	9	0	1.000	0.0650	9
3	Tamil Nadu	3	2	1.000	4.854	1
4	Rajasthan	3, 9	0	0.395, 0.605	0.4701	4
5	Karnataka	9	0	1.000	0.1212	8
6	Maharashtra	9	0	1.000	0.2424	6
7	Madhya Pradesh	9	0	1.000	0.4000	5
8	Uttar Pradesh	9	0	1.000	0.8889	3
9	Odisha	9	7	1.000	3.8437	2

Here the State with largest peer count is considered to be a most popular role model State in agricultural production. In the analysis it has been observed that the

1. **Odisha** appeared as an efficient peer state in the peer list of 7 inefficient States in agricultural Production.
2. **Tamil Nadu** appeared as an efficient peer of 2 inefficient states in agricultural production.

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Ground Nut Production State by State Analysis

State	Variable	Original value	Radial movement	Slack movement	Projected value	TE	SE
Gujarath	Yield	2670	0	0	2670	0.177	0.357
	Area	1.84	-1.513	-0.014	0.312		
	Production	4.92	-4.047	0	0.873		
Andhra Pradesh	Yield	890	0	485	1375	0.065	0.647
	Area	1.39	-1.13	-0.03	0.06		
	Production	1.23	-1.15	0	0.08		
Tamil Nadu	Yield	2812	0	0	2812	1	0.361
	Area	0.34	0	0	0.34		
	Production	0.96	0	0	0.96		
Rajasthan	Yield	1943	0	0	1943	0.47	0.384
	Area	0.47	-0.249	-0.05	0.171		
	Production	0.91	-0.482	0	0.428		
Karnataka	Yield	907	0	468	1375	0.121	0.66
	Area	0.73	-0.642	-0.028	0.06		
	Production	0.66	-0.58	0	0.08		
Maharastra	Yield	1217	0	158	1375	0.242	0.885
	Area	0.27	-0.205	-0.005	0.06		
	Production	0.33	-0.25	0	0.08		
Madhya Pradesh	Yield	990	0	385	1375	0.4	0.72
	Area	0.2	-0.12	-0.02	0.06		
	Production	0.2	-0.12	0	0.08		
Uttar Pradesh	Yield	896	0	479	1375	0.889	0.652
	Area	0.1	-0.011	-0.029	0.06		
	Production	0.09	-0.01	0	0.08		
Odisha	Yield	13750	0	0	1375	1	1
	Area	0.06	0	0	0.06		
	Production	0.08	0	0	0.08		

To measure the performance of the states, we ranked using the AP ranking method using VRTS environment. The **Tamil Nadu** state seems to be the best state in producing the output with the available input units and next **Odisha** producing more output comparing to other states. The following diagram explains the movement of the states performance in different environments.

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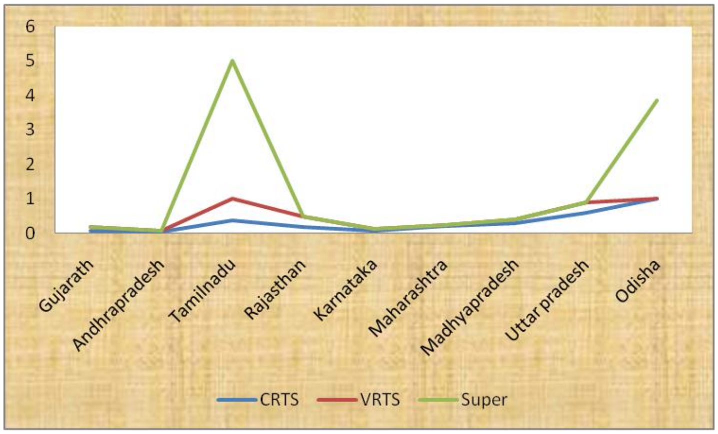

Fig: Super Efficiency

CONCLUSION

Researchers and clinicians alike may benefit from DEA. We hope this work will provide some insight on the usefulness of this technique for evaluating efficiency in environmental management and research in general. A variety of new models were presented in this review: basic and cross-efficiency models as well as ranking and hybrid qualitative/quantitative models. Assumptions and objectives were laid down. It was further shown by the fact that Odisha emerged as an efficient peer state on a list of seven agriculturally inefficient states. Environmentally based statistics on agricultural productivity showed Tamil Nadu to be an efficient counterpart to two unproductive states. Researchers and managers alike will appreciate the discussion on how to assess the findings. In-depth information was provided on the usage of supporting statistical and management decision-making tools. An industrial or business level study may be used to look at efficiency concerns. Efficiency may be used as a dependent variable to investigate why certain units are more efficient than others. It is possible to use both nonparametric and regression methods in these research. Managers may use the efficiency ratings to compare their performance to that of other similar units (benchmarking) or to aid in the selection of different projects and initiatives. DEA models might be improved by including managers' preferences into the equations, as well as their sensitivity to this inclusion.

Although DEA has many benefits, it also has certain drawbacks. To begin, the DEA models' output varies widely; some of these discrepancies are large. User familiarity with the model's capabilities and aims is essential. DEA model selection may lead to incorrect conclusions. Second, the DEA model's architecture has a significant impact on the final findings. For a given research topic or administrative decision, the proper inputs and outcomes must be selected. In many cases, the design is predicated on the availability of relevant data. Depending on the number of parameters, the number of efficient and inefficient units will vary. A study of this sensitivity is warranted. It's also possible to get different outcomes depending on the quantity of data you have. DEA is based on the analysis of data. It is possible that each new DMU will modify the whole data set. It's important to be thorough while estimating the results.

There is a lot more DEA literature that we haven't covered in our study. It's possible to analyse and implement a wide range of stochastic DEA models. DEA models may be selected more effectively if they are tested in a variety of contexts. There is still a need for further study on the advantages and disadvantages of different DEA models. Researchers may want to look at how DEA compares to other economic productive efficiency models, as well as its relevance from an environmental standpoint.

APPENDIX DATA

Table : Area, Production and Yield of Groundnut during 2013-14 in Major Producing States along with Coverage under Irrigation

Area- Million Hectors

State	Area	Production	Yield
Gujarath	1.84	4.92	2670
Andhra Pradesh	1.39	1.23	890
Tamil Nadu	0.34	0.96	2812
Rajasthan	0.47	0.91	1943
Karnataka	0.73	0.66	907
Maharashtra	0.27	0.33	1217
Madhya Pradesh	0.2	0.2	990
Uttar Pradesh	0.1	0.09	896
Odisha	0.06	0.08	1375

Production- Million Tons
Yield- Kg/Hector

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