Section A-Research paper
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Agricultural performance of Indian States and UTs based on Non-parametric Approach

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Abstract

Purpose: A non-parametric, linear programming method for assessing the relative effectiveness of the homogeneous decision maker units (DMUs) is data envelopment analysis . The agricultural performance of the Indian State and UT is discussed in this article. Here, the output parameters include production of rice, oil-seeds, sugarcane, pulses, wheat , and coarse cereals, whereas input parameters are yearly rainfall, GDP, the number of employees, population, and net cultivated area. To evaluate the agricultural productivity of India's states and union territories using the CCR, Input Oriented BCC, and Output Oriented BCC models.The efficacy scores of several models are compared and the super efficiency model is used to rank all of India's states and UTs.
Results: According to CCR model results, 74.19% of Indian states and UTs are efficient, whereasBCC models show 77.42% States and UTs are efficient. The most efficient unit is Madhya Pradesh, while the least inefficient unit is Kerala and the states ranked base on super efficiency score.
Limitation: Changing the quantity of inputs and outputs has an impact on the agricultural performance of the Indian States and UTs. Other environmental and social parameters can be used to assess agricultural sustainability. Comparison of qualitative variables is not allowed in the traditional DEA model.
Keywords:Data envelopment analysis, Agricultural Performance, CCR Model, BCC Model, Super efficiencymodel.

1. Introduction

Agriculture is an important sector of the economy of India. India has a 138 crore population, and 65.07% population lives in a rural areas in India. Approximately 60% of the Indian population works in the agriculture sector.In 2020–2021, the agriculture sector would contribute 20.19% of India's GDP. The agriculture sector is the third contribution to India's GDP in 2020-2021; one-third of our National income comes from agriculture.

Essential facts on the Problems of Indian Agriculture are the Indian farmers are dependent to a large extent on the monsoons, which are very uncertain, unequally distributed, and unreliable. The small holdings of the farmers do not encourage modern farming methods, like scientific cultivation, improved implements, and seeds. As returns are poor, a lot of time, labor, and power are wasted

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on small holdings. All the agricultural land cannot irrigate all the ground, and farmers depend on unpredictable monsoons. Therefore failure of monsoons leads to the loss of crops. There is also a shortage of good quality seeds, fertilizers, and cultivation techniques.
Characteristic Features of Indian Agriculture are It has a wide-ranging cultivated area for irrigation. Still, 30 percent of the total cultivated land possesses an irrigation facility, and 60-65 percent of farmland remains semi-arid. About 72.3 percent of the whole area is constant for food crops, yet the country is self-sustained for food demand.

Important and successful government Programs for the agriculture E-NAM The government is creating a gateway that will unify all of the APMC mandis and create a single market for all agricultural products. In 1998, the Indian government launched the Kisan Credit Card (KCC) to encourage farmers to buy agricultural inputs like seeds, fertilizers, and pesticides and to withdraw money for their output requirements. The KCC scheme was then expanded to include non-farm and related enterprises. On July 1, 2015, the Pradhan Mantri Krishi Sinchai Yojana (PMKSY) program was launched. The plan aims to reduce water waste, increase water efficiency, and guarantee irrigation. A government-sponsored scheme called the Pradhan Mantri Fasal Bima Yojana (PMFBY) offers crop insurance for the former. PM Kisan Samman Nidhi Yojana (PMKSNY), under this program, the Indian government sends 6,000 per year, in three installments of 2000 each, directly to the farmer's bank account via direct benefit transfer (DBT).

The NCF, presided over by Professor M.S. Swaminathan, released recommendations on November 18, 2004, on "land reforms, irrigation, credit and insurance, food security, employment, agricultural productivity, and farmer competitiveness". These suggestions boost productivity and the agricultural industry.It is based on a variety of variables, such as the accessibility and quality of farming inputs including land, water, seeds, and fertilizer, as well as the infrastructure for storage and sale, access to farm loans, and crop insurance. It also depends on the infrastructure for storage and sale.. IDEA2020 assessed a number of factors influencing post-harvest services and farm output in India and published a status report on the farm sector.

The remainder of the article is structured as follows: A detailed literature assessment on DEA usage in agriculture is provided in section (2). The approach we use to calculate the efficiency score and the whole ranking process are described in Section (3). Data collection and information on input and output data are covered in Section (4). Results and analysis of the agricultural performance of Indian states and UTs are included in Section (5). Finally, the last section discusses the conclusion and the research challenge for the future study.

2. Literature Review

A non-parametric, quantitative, unit-invariant mathematical linear programming approach called DEA is used to evaluate the effectiveness and performance of a set of DMUs that can handle various inputs and outputs. The DMUs were divided by DAE into two groups: the efficient group and the inefficient group, which may be estimated using the frontier curve, a combination of set-and-piecewise linear curves. If a DMU is on the frontier curve, it is said to be in the efficient group; otherwise, it is in the inefficient group. Charnes et al.[2] developed the linear programming technique based on Farrell work [3] to determine the efficiency score of the DMUs is called CCR model. After that, Banker et al.[4] worked on CCR model and developed the BCC model by adding extra convexity condition in CRR model. The application of DEA techniques [5, 6, 7, 8] has recently proved suc- cessful in a variety of fields, including supply chain management, information and communication technology (ICT), the health sector, finance, and agriculture, among others.

Dutta [9], offered some suggestions for management techniques and concepts to increase the output and profitability of agricultural production. Based on the frontier, Hasanov et al. [10]

used the DEA model to categories the productive and unproductive farms in the Zarafshan valley according to both technical and allocation efficiency. Suresh [11] to classify technical efficiency (TE) into pure technical efficiency (PTE) and scale efficiency for agricultural output across 409 Indian districts (SE).In order to evaluate the productivity of India's food grain production from 1960–1961 to 2013–2014 and identify the most productive year, Mathur et al. [12] used SFA and DEA. To investigate the Eco-efficiency of intensive agricultural production in 31 Chinese provinces, You et al. [13] used DEA and the Tobit model. According to the variables influencing Eco-efficiency, farming area per capita (FA), per capita income (IC), per capita population per home (PH), and per capita population burden coefficient (PB) all have statistically significant effects on overall efficiency. The CCR model was used by To evaluate allocative and technically inefficiency in wheat output onthree hundred farms in Punjab, India, between 1982 and 1983, Jha et al. [14]. In addition to using FDEA to rank and estimate paddy grower efficiency, Nandy et al. [15] used support vector machine (SVM) and random forest (RF) to identify the key factors influencing efficiency prediction. From 1976 to 2016, e Souza GdS et al. [16] studied at technical efficiency and sustainability in Brazilian agriculture. Wysokinski et al. [17] employed the unfavorable W-SBM-DEA model to determine the productivity of the EU-27 farming sector between 2008 – 2017. They employed input variables like agricultural acreage, labor, particular expenses, overheads, and depreciation, as well as desired output variables such as the total amount of GHG emissions, the total production of agricultural and livestock goods, and other undesirable output factors. China's agricultural production efficiency was evaluated using SFA from 2000 to 2015, according to [18]. When Pan et al. [19] examined the agricultural productivity of 11 provinces in the YREB from 2010 to 2019,they did so using a three-stage DEA Malmquist model. They found that overall factor productivity, technological advancement, and adjusted technical efficiency changes all rose.

Super-efficiency In reality, DEA models are highly helpful. Xue et al. [20] study the The significance of the super-efficiency DEA models' feasibility with respect to the DMUs' efficiency ranking are investigated. In this study, Seiford et al. [21] examine the impossibility of super-efficient DEA models in which the unit being evaluated is removed from the reference set. Due to the impossibility of super-efficiency DEA models, it is demonstrated that ranking the whole collection of efficient DMUs is impossible. Using the Malmquist productivity index, this study [22] examines the efficiency of water consumption in Shandong Province between 2006 and 2015. And According to data collected by Pan et al. [22] for the years 2006 to 2015, the water productivity in 17 cities in Shandong Province was positive in 2006–2007, 2007–2008, and 2013–2014; The water consumption productivity of 17 cities in Shandong Province is mostly influenced by technical change, as it was negative in the other time periods between 2006 and 2015 as well.

3. Methodology

DEA is an effective method for comparing homogeneous DMUs and classifying them into efficient and inefficient groups.DEA can handle many inputs and multiple outputs simultaneously without assuming a functional relationship between them, which is not allowed in regression mode. DEA is an LP problem that can be solved quickly using any traditional LP method. Therefore, DEA isa non-parametric, quantitative, unit invariant, data driven, LP approach that is used to assess therelative efficiency of homogeneous DMUs with numerous input-outputs. There are different types of DEA models that are developed based on constant return scales and variable return scales.

The Constant Return to Scale (CRS) has been extensively investigated and is advised for usein evaluating agriculture production in the CCR (Charnes, Cooper, and Rhodes) model [2]. Letus consider the whole system have n DMUs each having m inputs and q outputs. The input and output vector for $DMUj, j = 1, 2, 3, \cdots, n$ can be defined as $\alpha_j = (\alpha_{1j}, \alpha_{2j}, \alpha_{3j}, \ldots \alpha_{mj})' \in R^m$

And $\beta_j = (\beta_{1j}, \beta_{2j}, \beta_{3j}, \dots \beta_{qj})' \in R^q$. The input matrix X as $X = (\alpha_1, \alpha_2, \alpha_3, \dots \alpha_m) \in R^{m\times n}$ and the output matrix Y as $Y = (\beta_1, \beta_2, \beta_3, \dots \beta_q) \in R^{q\times n}$. the production possibility set defined as follows $T = \{(X, Y) \mid X \text{ can produce } Y\}$ and assume X>0 *and* $Y > 0$.

When constant returns to scale form of technology is assumed we have $T = T_{CCR}$ and

$$T_{CCR} = \{(\alpha, \beta): \alpha \geq \sum_{j=1}^{n} \gamma_j \alpha_j, 0 \leq \beta \leq \sum_{j=1}^{n} \gamma_j \beta_j, \qquad \gamma \geq 0\}$$

where $\gamma = (\gamma_1, \gamma_2, \dots \gamma_n) \in R^n$ is the intensity vector. The input oriented CCR model for $DMUo, (o = 1, 2, 3, \cdots, n)$ is defined as

$$\min \varphi_o \tag{1}$$

Subject to

$$\varphi_o \alpha_{io} \geq \sum_{j=1}^{n} \gamma_j \alpha_{ij}, \quad i = 1,2, \dots m$$

$$\beta_{ro} \leq \sum_{j=1}^{n} \gamma_j \beta_{rj}, \quad r = 1,2, \dots q$$

and

$$\gamma_j \geq 0, \quad \forall \ j = 1,2, \dots n$$

The optimal solution φ_o^* is the efficiency score for $DMUo$ for $o = 1, 2, \dots, n$.

Banker, Charnes and Cooper [4] in 1984 published the BCC model When variable returns to scale form of technology is assumed we have $T = T_{BCC}$ and

$$T_{BCC} = \{(\alpha, \beta): \alpha \geq \sum_{j=1}^{n} \gamma_j \alpha_j, 0 \leq \beta \leq \sum_{j=1}^{n} \gamma_j \beta_j, \sum_{j=1}^{n} \gamma_j = 1, \ \gamma \geq 0\}$$

where $\gamma = (\gamma_1, \gamma_2, \cdots, \gamma_n) \in R^n$ is the intensity vector. The input oriented BCC model for $DMUo$, $(o = 1, 2, 3, \cdots, n)$ is defined as

$$\min \varphi_o \tag{2}$$

Subject to

$$\varphi_o \alpha_{io} \geq \sum_{j=1}^{n} \gamma_j \alpha_{ij}, \quad i = 1,2, \dots m$$

$$\beta_{ro} \leq \sum_{j=1}^{n} \gamma_j \beta_{rj}, \quad r = 1,2, \dots q$$

$$\sum_{j=1}^{n} \gamma_j = 1$$

and

$$\gamma_j \geq 0, \quad \forall\ j = 1,2, \dots n$$

The output oriented BCC model for $DMUo$, $(o = 1, 2, 3, \cdots, n)$ is defined as

$$\max \varphi_o \tag{3}$$

Subject to

$$\alpha_{io} \geq \sum_{j=1}^{n} \gamma_j \alpha_{ij}, \quad i = 1,2, \dots m$$

$$\varphi_o \beta_{ro} \leq \sum_{j=1}^{n} \gamma_j \beta_{rj}, \quad r = 1,2, \dots q$$

$$\sum_{j=1}^{n} \gamma_j = 1$$

and

$$\gamma_j \geq 0, \quad \forall\ j = 1,2, \dots n$$

For ranking efficient units, Andersen and Petersen [26] created the super efficiency model in 1993. The super-efficiency model takes the form of a BCC model and thereby avoids the possibility of non-solution related with the convexity constraint in the CCR model [27]. The Input oriented super efficiency (Super-I) model is defined as

$$\min \varphi_o \tag{4}$$

Subject to

$$\varphi_o \alpha_{io} \geq \sum_{j=1, \neq 0}^{n} \gamma_j \alpha_{ij}, \quad i = 1,2, \dots m$$

$$\beta_{ro} \leq \sum_{j=1,\neq 0}^{n} \gamma_j \beta_{rj}, \quad r = 1,2,\ldots q$$

$$\sum_{j=1,\neq 0}^{n} \gamma_j = 1$$

and $$\gamma_j \geq 0, \quad \forall\ j = 1,2,\ldots n$$

Where $\gamma = (\gamma_1, \gamma_2, \cdots, \gamma_n)$ be a non-negative weight vector.

4. Data Collection

The study's data came from the official Indian government website. This study makes use of agricultural data collected at the state level between 2016 and 2017."State-wise annual rainfall (SR),total population (TP), total GDP, number of workers (NW), and net sown area (NA)" are the input variables that we use "production of rice (PR), wheat (PW), coarse cereals (PCC), pulses (PP), oil-seeds (PO), and sugarcane (PO) are the output variables (PS). The input data include things like rainfall in millimeters, net sown area in thousand hectares, workers in units, population in lanes, and gross domestic product in (corer) ". All output figures are expressed in thousand tonnes. The details of the input-output parameters listed in Table (1).

The DMUs for all tables in which the states and UTs of India were numerically represented are "(1) Andhra Pradesh, (2) Arunachal Pradesh, (3) Assam, (4) Bihar,(5) Chhattisgarh, (6) Delhi, (7) Goa, (8) Gujarat, (9) Haryana, (10) Himachal Pradesh, (11) Jammu & Kashmir, (12) Jharkhand, (13) Karnataka, (14) Kerala, (15) Madhya Pradesh, (16) Maharashtra, (17)Manipur, (18) Megha-laya, (19) Mizoram, (20) Nagaland, (21) Odisha, (22) Puducherry, (23) Punjab, (24) Rajasthan, (25) Sikkim, (26) Tamil Nadu, (27) Telangana, (28) Tripura, (29) Uttarakhand, (30) Uttar Pradesh, (31) West Bengal".

Table 1: **Variable used in the study**

Variable	Role	Details
state-wise annual rainfall	Input	Indian Meteorological Department [23]
Net sown area	Input	Ministry of Agriculture and Farmers Welfare [24].
Total population	Input	Economic Survey, Govt. of India [25].
GDP	Input	The Ministry of Statistics and Program Implementation [24].
Number of workers	Input	Annual Survey of Industries (ASI) [24].
Production of Rice	Output	Ministry of Agriculture and Farmers Welfare [24].
Production of Wheat	Output	Ministry of Agriculture and Farmers Welfare [24].
Production of Coarse cereals	Output	Ministry of Agriculture and Farmers Welfare [24].
Production of Pulse	Output	Ministry of Agriculture and Farmers Welfare [24].
Production of Oil seeds	Output	Ministry of Agriculture and Farmers Welfare [24].
Production of Sugarcane	Output	Ministry of Agriculture and Farmers Welfare [24].

5. Results and Discussion

The efficiency value of the DMUs lies between [0,1]. If any DMUs have the efficiency value 1, then it is efficient; otherwise, it is inefficient.This paper uses the state-wise agricultural data between 2016 and 17. In this paper, we calculate the efficiency by the CCR model, input and output oriented BCC model, and super efficiency model. In table(3), CCR represents the efficiency score by the CCR model, BCC-I represents the efficiency score by the input-oriented BCC model, BBC-O represents the efficiency score by output oriented BCC model, and super-I represents input oriented super-efficiency model.Table (3) shows that eight DMUs are inefficient by CCR efficiency score, and seven DMUs are inefficient by both BBC-I and BCC-O efficiency scores, overall thirty-one DMUs. Table (3) shows that Andhra Pradesh, Assam, Goa, Meghalaya, Odisha, and Tamil Nadu are inefficient states in all CCR, BCC-I, and BCC-O efficiency scores. But Jammu & Kashmir is an additional inefficient state in CCR efficiency score. In table (3), Super-I defined the ranking of states & UTs in the Indian agriculture sector. Then we find that Madhya Pradesh is first rank and Delhi is the last position in the Indian agriculture sector. The comparative analysis of states and UTs of efficiency score in figure (1).

Figure 1: Comparison of Efficiency Score in CCR, BCC-I and BCC-O

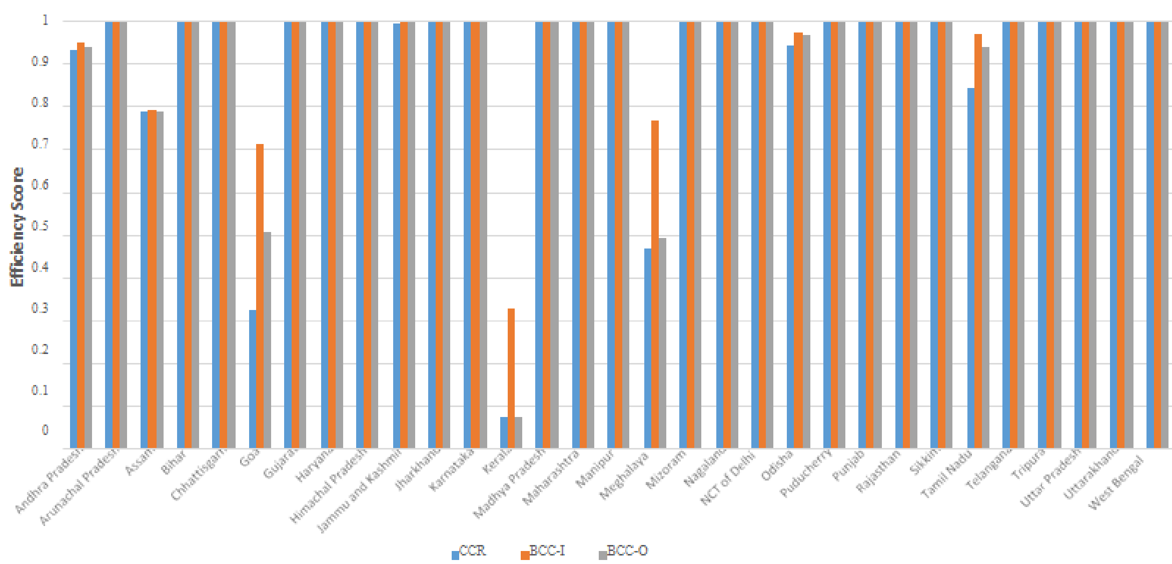

Table 2: Input and Output data

DMUs	SR	NA	NW	G.D.P.	TP	PR	PW	PCC	PP	PO	PS
1	760.4	6077	456946	697508	513.71	7452.4	0	1982	931	664.2	7830
2	2706.9	232	2569	19,627	14.59	220	7.7	102.5	13.1	36.6	37.7
3	2140.5	2774	181098	254478	331.68	4727.4	23.5	94.1	107.5	204.3	1207.2
4	1158	5293	98971	422316	1141.76	8239.3	5110.8	2719.1	461.7	125.9	13036
5	1315.8	4664	146551	254722	275.71	8048.4	159.5	357.5	758.7	169.9	848
6	567.9	22	75257	615605	186.77	17.3	87.2	6.7	0.1	4.5	0
7	3065.1	130	44576	63,460	15.12	113.2	0	0	5.9	4	40.2
8	604.9	10302	1246650	1153327	651.58	1930	2737	1937	818	4789.3	11950
9	392.9	3499	650051	556325	145.85	4453	11546.8	1087	75.9	964.5	8223
10	921.5	548	141772	125634	71.58	146.6	704.2	826.4	63.3	6.2	21.1
11	902.8	757	59028	125379	128.97	572.2	475.5	561	10.3	28.6	0
12	1264.0	1451	144620	236250	358.00	3841.8	425.2	590.8	806.5	264	512.9
13	849.9	9855	827665	1209136	642.29	2604.8	171	5281	1737.9	805.8	27378

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14	1870.9	2015	249935	634886	345.78	437.1	0	0.2	1.7	0.6	113.1
15	1203.2	15228	280373	648849	788.06	4226.8	17939.3	4766.9	6291.3	8224	4730
16	1272.8	16910	1365361	2188532	1187.27	3109.5	1875.1	6579	3768.1	5113.5	52262.4
17	1777.4	469	6942	21,294	30.12	430.4	5.6	58.8	30.3	32.3	348
18	2891.5	252	10517	27,439	31.29	203	0.9	44.4	11.8	14.9	0.4
19	2233.5	145	0	17,192	11.57	61.5	0	8.9	4.8	2.5	50.5
20	1364.9	385	5109	21,722	20.86	336.7	6.2	149.5	44.5	68.9	192.4
21	1253.5	4099	222789	393808	439.66	8325.9	0.1	256.2	479.1	121.2	344.3
22	655.6	15	37082	29,573	14.02	52.2	0	0.1	0.6	0.8	0
23	444.0	4130	531365	426988	291.40	11586.2	16440.5	477.2	33	57.8	7152
24	574.4	18169	412774	758809	742.40	452.7	8985.3	6734.5	3181.2	6240.2	488.7
25	2756.6	77	13372	20,687	6.44	19.7	0.4	75.9	5.5	6.4	0
26	534.6	4347	2003759	1302639	746.35	2369.4	0	1345.2	427.1	604.1	18987.6
27	1043.4	4774	605994	659033	364.62	5173.4	7	2768.2	536	723	2061
28	2381.9	255	23956	39,612	38.74	814.6	0.5	21.3	23.2	12.5	44.1
29	801.7	16564	783541	1248374	2160.87	13754	30056	3909	2184.4	1050.2	140169.2
30	1308.6	691	344376	195125	107.55	630	882	308	53	26	6477
31	1702.6	5246	497977	872527	950.79	15302.5	862.7	721.6	259.5	908.7	1549.7

Table 3: Efficiency Score in CCR, BBC-I, BCC-O and Super-I

DMUs	CCR	BCC-I	BCC-O	Super-I	Ranking
1	0.9351	0.9509	0.9398	0.950929171	25
2	1	1	1	1.324058332	15
3	0.7901	0.7937	0.7905	0.793662177	27
4	1	1	1	3.321456682	6
5	1	1	1	1.598612375	13
6	1	1	1	0.013828401	31
7	0.3257	0.7126	0.5077	0.712616386	29
8	1	1	1	1.187556624	20
9	1	1	1	1.023211564	23
10	1	1	1	2.340572528	8
11	0.9951	1	1	1.09839681	22
12	1	1	1	2.017824995	10
13	1	1	1	1.307346386	16
14	0.0748	0.3302	0.0748	0.330166155	30
15	1	1	1	7.464979673	1
16	1	1	1	1.148258586	21
17	1	1	1	1.194061406	19
18	0.4717	0.7672	0.4943	0.767249761	28
19	1	1	1	1.726633965	11

20	1	1	1	1.639012649	12
21	0.9428	0.9735	0.9676	0.973541095	24
22	1	1	1	4.87049835	3
23	1	1	1	4.275225383	4
24	1	1	1	2.908648622	7
25	1	1	1	2.255665441	9
26	0.8457	0.9725	0.9403	0.834703532	26
27	1	1	1	1.296044902	17
28	1	1	1	1.463359313	14
29	1	1	1	5.333989508	2
30	1	1	1	1.246709861	18
31	1	1	1	3.523222793	5

6. Conclusion

Production of agricultural products affects a region's growth either directly or indirectly. One of the difficult tasks for policymakers is to increase the output of agricultural products while utilising the resources at hand. He may use DEA to compare the production of various regions and make the appropriate decisions and moves to increase the productivity of under-performing regions. In order to evaluate India's agriculture industry in 2016–17, this study used the CCR, BCC–I, and BCC–O models to investigate the influence of inputs and outputs. Our primary goal is to determine relative efficiency based on minimizing input while maintaining the same level of output or maximizing production while utilizing a fixed input, which will assist policymakers in improving the agricultural performance of the inefficient state and UT. According to CCR model results, 74.19% of Indian states and UTs are efficient, whereas BCC models show 77.42% States and UTs are efficient. The most efficient unit is Madhya Pradesh, while the least inefficient unit is Kerala. It is impossible to rank the efficient states and UTs in the CCR and BCC models because the efficient states and UTs have an efficiency score of 1. To resolve this problem, we used super efficiency model and completely ranked the states and UTs of India. The addition of some inputs and outputs data might have an influence on the efficiency scores of states and UTs. It would appear essential that further measures be taken to enhance the efficiency of the states and UTs, such as public works initiatives and a proper programme for rural infrastructure growth.

It is necessary to do further study on the state's and the UTs' agricultural productivity through-out a range of time periods. The states and UTs might not create all of the output, as they might not provide outputs that are comparable. In this case, a non-homogeneous DEA model may be used to assess the performance of the states and UTs. Also, The input-output data may occasionally be unavailable or incomplete, or they may occasionally be of a qualitative character. The Fuzzy DEA model may be used to manage this kind of problem. For instance, a variety of environmental effects—outside of global warming—have regionally specific effects on soil, water, and air that affect the productivity of the states and UTs.

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