

ENERGY EFFICIENCY ASSESSMENT OF AGRICULTURE SECTOR IN INDIA USING FUZZY DATA ENVELOPMENT ANALYSIS

Aditi Garg^{1*}, Smita Verma²

¹Department of Applied Mathematics and Computational Science, Shri Govindram Seksaria Institute of Technology and Science (SGSITS) 23, Sir M. Visvesvaraya Marg, Vallabh Nagar, Indore, Madhya Pradesh 452003, India; gargaditi53@gmail.com

² Department of Applied Mathematics and Computational Science, Shri Govindram Seksaria Institute of Technology and Science (SGSITS) 23, Sir M. Visvesvaraya Marg, Vallabh Nagar, Indore, Madhya Pradesh 452003, India; yvsmita@gmail.com

* Correspondence: gargaditi53@gmail.com

Abstract

The agriculture sector of India is growing at a fast pace, owing to the increasingly rising food demand and technology usage in the developing sector. Since the last 10 years energy consumption in India has increased by a compound annual growth rate of 4.11%. This continuous rise in consumption of energy may be attributed to rising population and increasing per capita income of the country. The industry sector provided the most to the total amount of energy used in 2020–2021 (41.09%), followed by the domestic sector (25.67%), agricultural (17.52%), and the commercial sector (8.31%). In this paper we have measured the energy efficiency of crop production sector of India using Fuzzy Data Envelopment Analysis. In this regard, 20 Indian states are selected as the study area for the period 2015-20. The Fuzzy Data envelopment analysis (DEA) variable returns to scale (VRS) with input orientation has been used for efficiency measurement of the DMUs. The results of our study show that only three states out of the 20 states were found to be energy efficient every year for the period 2019-2020.

Keywords: Fuzzy DEA, Energy efficiency, VRS, Linear programming, Sustainability

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INTRODUCTION

Data Envelopment Analysis (DEA) is initially developed by Charnes et al. in 1978[[1]] as a linear programming based nonparametric technique for evaluating the relative efficiencies of a homogeneous set of DMUs which utilize multiple inputs to produce multiple outputs. A variety of DEA models with some extensions and applications have been reported in Cooper et al. 2007[[8]]. The CCR model given by Charnes et al. in 1978 and the BCC model by Banker et al. in 1984[[5]] are some standard DEA models which were initially formulated to measure the efficiency of Decision-Making Units (DMUs) with accurate and certain inputs and outputs values. But, in some cases input and output data can't be precisely measured, for example: quality of service, quality of input resource, degree of satisfaction, unavailability of information etc. In such cases, the data with crisp numbers will not satisfy the real needs and the restriction will diminish practical flexibility of DEA in application. Thus, If the efficiency measures are expressed by membership functions rather than crisp values, more information is provided and by extending to fuzzy environment, the DEA approach is made more powerful in application. In this study we have attempted to measure the Energy efficiency measurement of 20 major crop producing states of India for the period 2019-2020 using a Fuzzy DEA model BCC input-oriented model.

To deal with imprecise data, the notion of fuzziness was introduced in DEA and the DEA was extended to fuzzy DEA (FDEA). Cooper et al. [[8]] were the first who addressed the problem of imprecise data in DEA. Cooper et al. asserted that the term "imprecise data" reflects the situation where some input-output data are known only to the extent that the true values lie within bounded intervals while other data are known only in terms of ordinal relations and proposed imprecise DEA (IDEA). The resulting DEA model is a linear programming model which is developed through a series of scale transformations and variable alterations, and it produces the final efficiency score as a deterministic numerical value less than or equal to one. It is argued that when the data are imprecise, the final efficiency score should also be imprecise, i.e., it should also appear in ranges. The literature on FDEA can also be seen in Kao et al. Kao, C., & Liu, S. T. (2000). Fuzzy efficiency measures in data envelopment analysis Fuzzy Sets and Systems, 113, 427-437.; Wang et al. [[30]]; Hatami-Marbini et al. [[12]]; Angiz et al. [[3]]; Emrouznejad et al. [[9]] and others.

OBJECTIVES AND METHODOLOGY

In the IEA's 2018 report, energy demand in 2017 was 584 exajoules (EJ) and is forecasted to rise 26% to 736 EJ in 2040. According to the U.S. Energy Information Administration, global energy consumption will increase by 48% by 2040, contributing to almost 26% of greenhouse gas emissions. The world, therefore, is rising to the challenge of increased energy demand and the derived requirement of energy resources. Additionally, hugely increasing energy consumption causes many issues, for example, greenhouse gas emissions. Consequently, cutting back the consumption of global energy has become very crucial, with energy efficiency improvement being one of the most effective tools.

The two most commonly applied basic DEA models are CCR model, named after Charnes Cooper and Rhodes (1978) and BCC model, named after Banker, Charnes, and Cooper (1984). These two models obtain efficiency measures under constant returns to-scale (CRS) and variable returns-to-scale (VRS) assumptions. The BCC model is one of the extensions of the CCR model where the efficient frontiers set is represented by a convex curve passing through all efficient DMUs. DEA can be either input or output-orientated. In the first case, the DEA method defines the frontier by seeking the maximum possible proportional reduction in input usage, with output levels held constant, for each DMU. However, for the output-orientated case, the DEA method seeks the maximum proportional increase in output production, with input levels held fixed.

Fuzzy set theory is a generalization of classical set theory in that the domain of the characteristics function is extended from the discrete set $\{0, 1\}$ to the closed real interval $[0, 1]$. Zadeh (Zadeh, L.A. (1965). Fuzzy sets, Information and Control 8, 338-353. defined a fuzzy set as a class of objects with continuum grades of membership. Suppose X is a space of objects, and x is a generic element of X . A fuzzy set A , in X can be defined as the set of ordered pairs: $A = \{(x, u_A(x)) \mid x \in A\}$ where $u_A(x): X \rightarrow M$ is the membership function and M is the membership space that varies in the interval $[0, 1]$. The closer the value of $u_A(x)$ is to one, the greater the membership degree of X to A . Zadeh (1978) suggested that fuzzy sets could be used as a basis for the theory of possibility similar to the way that measurement theory provides the basis for the theory of probability. The fuzzy variable is associated with a possibility distribution in the same manner that a random variable is associated with a probability distribution. Therefore, the computed fuzzy efficiency scores are viewed as a fuzzy variable in the range $[0, 1]$. The FDEA approach makes it possible to convert fuzzy data into interval data that can be integrated into the DEA framework and analyzed using the linear programming mode. Several approaches have been developed to deal with fuzzy input and output data in FDEA. Hatami-Marbini et al. [[12]] classified them as: (i) tolerance approach, (ii) α -cut approach, (iii) fuzzy ranking approach and (iv) possibility approach. Among these approaches, α -cut approach has been widely used to solve FDEA models.

The DEA model proposed by Charnes et al. assumes a constant return to scale. Banker et al. [[5]] modify the model of Charnes et al. to suit for cases of variable returns to scale. One form of their model is

$$E_r = \max \frac{\sum_{k=1}^t u_k Y_{rk}}{v_0 + \sum_{j=1}^s v_j X_{rj}}$$

$$\text{s.t. } \frac{\sum_{k=1}^t u_k Y_{ik}}{v_0 + \sum_{j=1}^s v_j X_{ij}} \leq 1, i = 1, \dots, n$$

$$u_k, v_j \geq \varepsilon > 0, v_0 \text{ unconstrained in sign,}$$

where X_{ij} and Y_{ik} represent input and output data for the i th DMU with j ranging from 1 to s and k from 1 to t , and ε is a small non-Archimedean quantity. Index r indicates the DMU to be rated, and there are n DMUs. When v_0 is set to 0, the assumption of constant returns to scale is imposed, and the model becomes that of Charnes et al. Note that Model (1) is a linear fractional program which can be transformed to a linear programming linear program:

$$E_r = \max \sum_{k=1}^t u_k Y_{rk}$$

$$\text{s.t. } v_0 + \sum_{j=1}^s v_j X_{rj} = 1$$

$$\sum_{k=1}^t u_k Y_{ik} - \left(v_0 + \sum_{j=1}^s v_j X_{ij} \right) \leq 0, i = 1, \dots, n$$

$u_k, v_j \geq \varepsilon > 0, v_0$ unconstrained in sign.

Therefore, the conventional LP method can be applied to solve E_r .

Fuzzy DEA

In a set of DMUs, suppose the inputs \tilde{X}_{ij} and outputs \tilde{Y}_{ik} are approximately known and can be represented by fuzzy sets with membership functions $\mu_{\tilde{X}_{ij}}$ and $\mu_{\tilde{Y}_{ik}}$, respectively. Without loss of generality, we will assume that

all observations are fuzzy, since crisp values can be represented by degenerated membership functions which only have one value in their domain. Hence, a fuzzy DEA model can be formulated as

$$\begin{aligned} \tilde{E}_r &= \max \sum_{k=1}^t \frac{u_k \tilde{Y}_{rk}}{(v_0 + \sum_{j=1}^s v_j \tilde{X}_{rj})} \\ \text{s.t.} \quad &\sum_{k=1}^t \frac{u_k \tilde{Y}_{ik}}{(v_0 + \sum_{j=1}^s v_j \tilde{X}_{ij})} \leq 1, \quad i = 1, \dots, n \\ &u_k, v_j \geq \varepsilon > 0, v_0 \text{ unconstrained in sign.} \end{aligned} \quad (3)$$

(1)

Let $S(\tilde{X}_{ij})$ and $S(\tilde{Y}_{ik})$ denote the support of \tilde{X}_{ij} and \tilde{Y}_{ik} . The α -cuts of \tilde{X}_{ij} and \tilde{Y}_{ik} are defined as

$$(X_{ij})_\alpha = \{x_{ij} \in S(\tilde{X}_{ij}) \mid \mu_{\tilde{X}_{ij}}(x_{ij}) \geq \alpha\}, \quad \forall i, j,$$

$$(Y_{ik})_\alpha = \{y_{ik} \in S(\tilde{Y}_{ik}) \mid \mu_{\tilde{Y}_{ik}}(y_{ik}) \geq \alpha\}, \quad \forall i, k.$$

Note that $(X_{ij})_\alpha$ and $(Y_{ik})_\alpha$ are crisp sets. Using α -cuts, also called α -level sets, the inputs and outputs can be represented by different levels of confidence intervals. The fuzzy DEA model is thus transformed to a family of crisp DEA models with different α -level sets $\{(X_{ij})_\alpha \mid 0 < \alpha \leq 1\}$ and $\{(Y_{ik})_\alpha \mid 0 < \alpha \leq 1\}$. These sets represent sets of movable boundaries, and they form nested structures for expressing the relationship between ordinary set and fuzzy sets [15].

The α -level sets defined in Eqs. (4a) and (4b) are crisp intervals which can be expressed in the form:

$$\begin{aligned} (X_{ij})_\alpha &= \left[\min_{x_{ij}} \{x_{ij} \in S(\tilde{X}_{ij}) \mid \mu_{\tilde{X}_{ij}}(x_{ij}) \geq \alpha\}, \max_{x_{ij}} \{x_{ij} \in S(\tilde{X}_{ij}) \mid \mu_{\tilde{X}_{ij}}(x_{ij}) \geq \alpha\} \right], \\ (Y_{ij})_\alpha &= \left[\min_{y_{ik}} \{y_{ik} \in S(\tilde{Y}_{ik}) \mid \mu_{\tilde{Y}_{ik}}(y_{ik}) \geq \alpha\}, \max_{y_{ik}} \{y_{ik} \in S(\tilde{Y}_{ik}) \mid \mu_{\tilde{Y}_{ik}}(y_{ik}) \geq \alpha\} \right]. \end{aligned}$$

Based on Zadeh's extension principle [28,30,31], the membership function of the efficiency of DMU r can be defined as

$$\mu_{E_r}(z) = \sup_{\mathbf{x}, \mathbf{y}} \min \{ \mu_{\tilde{X}_{ij}}(x_{ij}), \mu_{\tilde{Y}_{ik}}(y_{ik}), \forall i, j, k \mid z = E_r(\mathbf{x}, \mathbf{y}) \}, \quad (6)$$

where $E_r(\mathbf{x}, \mathbf{y})$ is defined in (1). The approach for constructing the membership function μ_{E_r} , proposed in this paper is to derive the α -cuts of μ_{E_r} . According to Eq. (6), μ_{E_r} is the minimum of $\mu_{X_{ij}}(x_{ij}), \mu_{Y_{ik}}(y_{ik}), \forall i, j, k$; we need $\mu_{\tilde{X}_{ij}}(x_{ij}) \geq \alpha, \mu_{\tilde{Y}_{ik}}(y_{ik}) \geq \alpha$, and at least one $\mu_{\tilde{X}_{ij}}(x_{ij})$ or $\mu_{\tilde{Y}_{ik}}(y_{ik})$ equal to $\alpha, \forall i, j, k$ such that $z = E_r$ to satisfy $\mu_{E_r}(z) = \alpha$. Since all α -cuts form a nested structure with respect to α : i.e., given $0 < \alpha_2 < \alpha_1 \leq 1$, we have $[(X_{ij})_{\alpha_1}^L, (X_{ij})_{\alpha_1}^U] \subseteq [(X_{ij})_{\alpha_2}^L, (X_{ij})_{\alpha_2}^U]$ and $[(Y_{ik})_{\alpha_1}^L, (Y_{ik})_{\alpha_1}^U] \subseteq [(Y_{ik})_{\alpha_2}^L, (Y_{ik})_{\alpha_2}^U]$; therefore, $\mu_{X_{ij}}(x_{ij}) \geq \alpha$ and $\mu_{\tilde{X}_{ij}}(x_{ij}) = \alpha$, and $\mu_{Y_{ik}}(y_{ik}) \geq \alpha$ and $\mu_{\tilde{Y}_{ik}}(y_{ik}) = \alpha$, respectively, have the same domain. To find the membership function of μ_{E_r} , it suffices to find the lower and upper bounds of the α -cut of μ_{E_r} , which, based on Eq. (6), can be solved as

$$\begin{aligned} (E_r)_\alpha^L &= \min E_r(\mathbf{x}, \mathbf{y}) \\ \text{s.t.} \quad &(X_{ij})_\alpha^L \leq x_{ij} \leq (X_{ij})_\alpha^U, \quad \forall i, j \\ &(Y_{ik})_\alpha^L \leq y_{ik} \leq (Y_{ik})_\alpha^U, \quad \forall i, k \\ (E_r)_\alpha^U &= \max E_r(\mathbf{x}, \mathbf{y}) \\ \text{s.t.} \quad &(X_{ij})_\alpha^L \leq x_{ij} \leq (X_{ij})_\alpha^U, \quad \forall i, j \\ &(Y_{ik})_\alpha^L \leq y_{ik} \leq (Y_{ik})_\alpha^U, \quad \forall i, k \end{aligned}$$

or in full form:

$$(E_r)_\alpha^L = \min_{\substack{(X_{ij})_\alpha^L \leq x_{ij} \leq (X_{ij})_\alpha^U \\ (Y_{ik})_\alpha^L \leq y_{ik} \leq (Y_{ik})_\alpha^U \\ \forall i, j, k}} \left\{ \begin{aligned} E_r &= \max \sum_{k=1}^t \frac{u_k Y_{rk}}{\left(v_0 + \sum_{j=1}^s v_j X_{rj} \right)} \\ \text{s.t.} \quad &\sum_{k=1}^t \frac{u_k Y_{ik}}{\left(v_0 + \sum_{j=1}^s v_j X_{ij} \right)} \leq 1, \quad i = 1, \dots, n \\ &u_k, v_j \geq \varepsilon > 0, v_0 \text{ unconstrained in sign.} \end{aligned} \right.$$

$$(E_r)_\alpha^L = \max_{\substack{(X_{ij})_\alpha^L \leq x_{ij} \leq (X_{ij})_\alpha^U \\ (Y_{ik})_\alpha^L \leq y_{ik} \leq (Y_{ik})_\alpha^U \\ v_{i,j,k}}} \left\{ \begin{array}{l} E_r = \max \sum_{k=1}^t u_k Y_{rk} / \left(v_0 + \sum_{j=1}^s v_j X_{rj} \right) \\ \text{s.t.} \sum_{k=1}^t u_k Y_{ik} / \left(v_0 + \sum_{j=1}^s v_j X_{ij} \right) \leq 1, i = 1, \dots, n \\ u_k, v_j \geq \varepsilon > 0, v_0 \text{ unconstrained in sign.} \end{array} \right.$$

The two-level mathematical model can be simplified to the conventional one-level model by reasoning as follows. When the inputs and outputs of every DMU vary in ranges, to find the smallest relative efficiency of a DMU compared with other DMUs, one will set the output level of this DMU and the input levels of all other DMUs to their lowest values and set the input level of this DMU and the output levels of all other DMUs to their highest values ([14] On the contrary, to find the highest relative efficiency of a DMU, one will set the output level of this DMU and the input levels of all other DMUs to their highest values and set the input level of this DMU and the output levels of all other DMUs to their lowest values. Therefore, Models (8a) and (8b) become

$$(E_r)_\alpha^L = \max \sum_{k=1}^t \frac{u_k (Y_{rk})_\alpha^L}{(v_0 + \sum_{j=1}^s v_j (X_{rj})_\alpha^U)}$$

$$\text{s.t.} \sum_{k=1}^t \frac{u_k (Y_{rk})_\alpha^L}{(v_0 + \sum_{j=1}^s v_j (X_{rj})_\alpha^U)} \leq 1$$

$$\sum_{k=1}^t \frac{u_k (Y_{ik})_\alpha^U}{(v_0 + \sum_{j=1}^s v_j (X_{ij})_\alpha^L)} \leq 1, i = 1, \dots, n, i \neq r$$

$$u_k, v_j \geq R > 0, v_0 \text{ unconstrained in sign.}$$

$$(E_r)_\alpha^U = \max \sum_{k=1}^t \frac{u_k (Y_{rk})_\alpha^U}{(v_0 + \sum_{j=1}^s v_j (X_{rj})_\alpha^L)}$$

This pair of mathematical programs involves

$$\text{s.t.} \sum_{k=1}^t \frac{u_k (Y_{rk})_\alpha^U}{(v_0 + \sum_{j=1}^s v_j (X_{rj})_\alpha^L)} \leq 1$$

$$\sum_{k=1}^t \frac{u_k (Y_{ik})_\alpha^L}{(v_0 + \sum_{j=1}^s v_j (X_{ij})_\alpha^U)} \leq 1, i = 1, \dots, n, i \neq r$$

$$u_k, v_j \geq \varepsilon > 0, v_0 \text{ unconstrained in sign.}$$

the systematic study of how the optimal solutions change as $(X_{ij})_2^L, (X_{ij})_a^U, (Y_{ik})_2^L$, and $(Y_{ik})_z^U$ vary over the interval $\alpha \in (0,1)$, they fall into the category of parametric programming [12].

If both $(E_r)_z^L$ and $(E_r)_s^U$ are invertible with respect to α , then a left shape function $L(z) = [(E_r)_z^L]^{-1}$ and a right shape function $R(z) = [(E_r)_s^U]^{-1}$ can be obtained. From which the membership function μ_{E_r} is constructed:

$$\mu_{E_r}(z) = \begin{cases} L(z), & z_1 \leq z \leq z_2, \\ 1, & z_2 \leq z \leq z_3, \\ R(z), & z_3 \leq z \leq z_4, \end{cases}$$

Otherwise, the set of intervals $\{[(E_r)_\alpha^L, (E_r)_\alpha^U] \mid \alpha \in (0,1)\}$ still reveals the shape of μ_{E_r} , although the exact function form is not known explicitly.

RESULT AND CONCLUSION

Since the very Independence of India, its focus has been on making the country self-sustainable in terms of food production and thus the five-year plans and the subsidies to Minimum support price, all work towards the increasing crop production and farmer welfare in the country. But, today being self-sustainable in terms of energy is a huge challenge for the country due to the growing population and stress on food production. This study shows that only three out of the 20 states are found to be energy efficient in crop production in India namely, Uttar Pradesh, Jammu & Kashmir and Himachal Pradesh. Among the worst performing states are Rajasthan, Chhattisgarh and Odisha. We hope this study will provide an insight to policy makers and poor performing states thereby adopting measures to increase their efficiency and move towards a sustainable production. Fig1 and Fig2 below give the most likely and least likely efficiency scores obtained.

Fig1

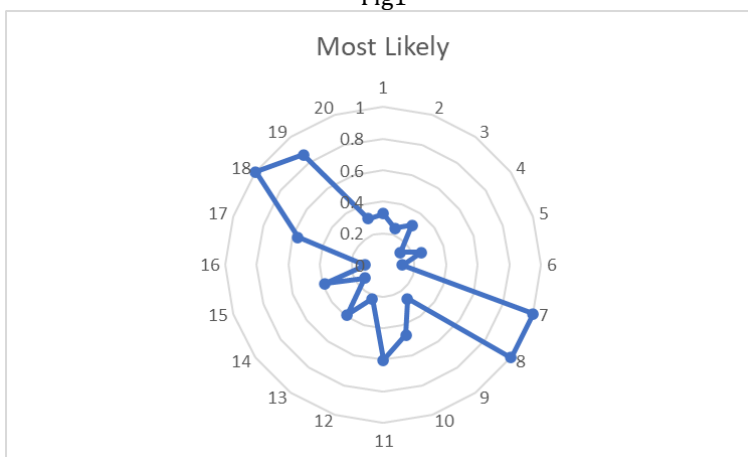


Fig2

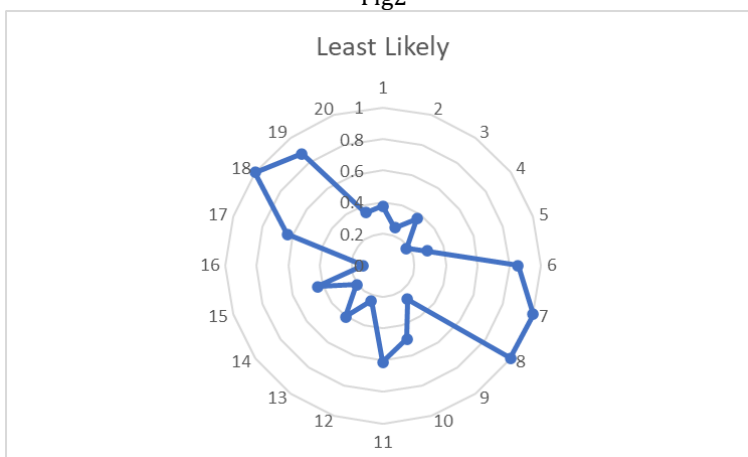


Table 1
Data and the most likely and least likely efficiency scores

	INPUTS				OUTPUTS	Efficiency Scores $\alpha=0$	
	Area	Fertilizers (N)	Electricity (Gwh)	Labour		Most Likely	Least Likely
DMU							
Andhra Pradesh	7250.80	64880.00	191726500000.00	169677554.00	34235293.00	0.32324	0.37466
Assam	3323.00	12920.280	462500000.00	1845346.00	9271590.91	0.245	0.24861
Bihar	6981.90	81704.060	11661750000.00	18345649.00	32591110.00	0.31027	0.3641
Chhattisgarh	5614.00	29741.830	63529375000.00	5091882.00	7944944*	0.13632	0.18347
Gujarat	10354.00	85746.540	149872875000.00	6839415.00	37175841.00	0.25702	0.29251
Haryana	6405.90	70745.990	129639500000.00	1528133.00	29113929.5*	0.12092	0.85565
Himachal Pradesh	765.30	2532.500	709125000.00	175038.00	1751142.89	1	1
Jammu and Kashmir	888.70	3361.230	4600000000.00	547705.00	18763141.97*	1	1
Jharkhand (es)	3005.60	8723.870	2423875000.00	4436052.00	5680543.10	0.26311	0.2652
Karnataka	12242.70	67303.400	272788375000.00	7155963.00	65223913.49	0.46466	0.49048
Kerela	1352.20	5242.920	4505875000.00	132285.00	9589931.52	0.60361	0.61285
Madhya Pradesh	29419.20	110656.190	287711750000.00	12192267.00	74138811.38	0.22608	0.23627
Maharashtra	21143.00	103241.890	366140375000.00	13486140.00	88690519.95	0.38886	0.40178
Odisha	5355.60	23030.610	7239375000.00	6739993.00	8304408.01*	0.1429	0.20596
Punjab	7210.90	99196.110	144769500000.00	1588455.00	38335788.00	0.38641	0.43707
Rajasthan	24319.20	80528.760	320809375000.00	4939664.00	37722519.65	0.11185	0.12692
Tamil Nadu	5230.80	38513.320	172853250000.00	9606547.00	40051153.43	0.56808	0.63732
Uttar Pradesh	24319.20	247378.810	227500625000.00	199939223.00	237821288.00	1	1
Uttarakhand	944.70	8192.760	2391875000.00	403301.00	9010708.00	0.86	0.87225
West Bengal	8508.50	52255.230	17484375000.00	10188842.00	36862609.94	0.30879	0.35204

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