Available online at http://ijdea.srbiau.ac.ir

Int. J. Data Envelopment Analysis (ISSN 2345-458X)

Vol. 13, No. 1, Year 2025 Article ID IJDEA-00422, Pages 29-46
Research Article

International Journal of Data Envelopment Analysis

Science and Research Branch (IAU)

Transforming Regional Resource Management through Distinct Development Coefficients: A Practical Application on Advanced Sustainable Development Indicators

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Received 12 June 2024, Accepted 27 December 2024

Abstract

This study investigates centralized resource allocation (CRA) within the framework of Data Envelopment Analysis (DEA), applying a previously proposed model from [1] to real-world data from 17 East Asian and Pacific countries based on 2015 statistics. The countries were selected according to the completeness of data from the World Development Indicators (WDI), involving five input and three output indicators related to sustainable development, agricultural infrastructure, and energy infrastructure. To better capture regional differences, heterogeneity in output growth coefficients was considered using the coefficient of variation and inter-indicator relationships. While the core DEA model is adopted from previous literature, the main contribution of this study lies in its empirical application to a new regional context, offering policy-relevant insights and practical implications. Results show that applying the proposed model enables significant resource savings without compromising key outputs. Furthermore, the allocated resources moved countries closer to the efficient frontier, supporting balanced and sustainable development. These findings provide valuable guidance for policymakers in resource planning and sustainable growth across the energy and agricultural sectors.

Keywords: Data Envelopment Analysis, Centralized Resource Allocation, Sustainable Development, Energy Infrastructure, East Asia and the Pacific.

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1. Introduction

Data Envelopment Analysis (DEA) is a non-parametric, precise, and widely used method in operations research and economics, applied to assess the relative efficiency of decision-making units (DMUs). By systematically distinguishing efficient units from inefficient ones, DEA provides a robust framework for identifying performance bottlenecks and enhancing productivity. One of the major advancements in this field is the development of centralized resource allocation models, which, through an integrated framework, aim to optimize the distribution of resources across multiple DMUs while targeting the overall efficiency of the system. In centralized DEA, a central decision-making unit evaluates the total inputs and outputs of all DMUs and optimally allocates input resources based on the needs and scale of each unit. The objective of this model is to reduce the overall input consumption while maintaining or increasing the total output, thereby improving the overall system performance. These models are typically implemented by solving a single linear programming problem, resulting in all units being projected onto the efficiency frontier. The DEA method was introduced in [2] as a linear programming approach for evaluating the efficiency of DMUs through the estimation of production frontiers. This method, which introduced the constant returns to scale (CCR) model, has been widely applied for performance measurement in public programs. Subsequently, the variable returns to scale (VRS) model was developed in [3], allowing for a more refined assessment of DMU performance under non-constant returns to scale and addressing both technical and scale efficiency. The concept of centralized resource allocation within DEA, in which optimal targets are set for each decision-making unit, was first proposed in [4]. This model focuses on two key features: the position of units relative to the efficiency frontier and the optimization of total inputs and outputs by finding weights that maximize relative efficiency. The model is based on a multiplier approach that optimally adjusts the aggregation of inputs and outputs. Sustainable development is defined as meeting the needs of the present generation without compromising the ability of future generations to meet their own needs. This concept is critically important across all sectors, particularly in energy and agriculture, which constitute the backbone of food and energy security in any nation. Energy infrastructure plays a pivotal role in ensuring the sustainable and efficient supply of energy resources. The advancement of clean and modern infrastructure—such as smart grids and the deployment of renewable energy sources—contributes significantly to reducing environmental pollutants, improving energy efficiency, and promoting long-term sustainability of the energy system. In parallel, agricultural infrastructure encompasses elements such as advanced irrigation techniques, effective soil management, and the responsible use of fertilizers and pesticides. These practices help increase agricultural productivity while preserving ecosystems and natural resources. At the international level, the optimal allocation of resources among nations, especially in critical sectors like energy and agriculture, is essential for realizing global sustainable development goals. Such allocation must be conducted in a manner that allows countries with limited capacities to enhance their infrastructure and operational efficiency, while more developed nations assume leading roles in technology transfer and financial support.

Integrating the concepts of optimal resource allocation with sustainable development indicators—especially within DEA models—can help identify the most efficient strategies for infrastructure investment and development. This integration supports policymakers in making optimal decisions to enhance both the economic and environmental performance of countries. Here are several key references related to sustainable development in the fields of energy, agriculture, and resource allocation. In the literature review section, several studies on sustainable development, energy consumption optimization, increasing agricultural productivity, and the advancement of environmental policies have been mentioned.

In many real-world systems, input and output indicators do not exhibit uniform development rates, and their rates of change vary throughout the development process. In other words, the assumption of uniform returns to scale for all indicators, as used in classical DEA models, is not always applicable in practical settings. This highlights the need to revise the traditional concept of returns to scale. In this study, output indicators are divided into two categories: those assumed to have development rates similar to inputs, and those with distinctively higher development coefficients. Since DEA models are built upon fundamental principles and assumptions, this situation called for an extension of the returns to scale concept and the introduction of a new principle, as proposed in [5], to enhance the dynamism and realism in the performance analysis of systems.
This study seeks to address the following key questions:

How can the performance of countries on the path toward sustainable development be evaluated using the DEA approach, while accounting for unequal development coefficients among input and output indicators? When certain output indicators exhibit significantly higher development coefficients, how should resources be optimally allocated among countries in a way that conserves overall inputs while maintaining or enhancing total output growth? What is the impact of employing a centralized resource allocation model—alongside a revised returns to scale principle—on identifying countries with the greatest potential for improvement and on designing effective development policies?

The primary objective of this study is to develop a robust DEA-based framework for evaluating national performance in the context of sustainable development. This framework incorporates asymmetric development coefficients for inputs and outputs, with a particular focus on output indicators that exhibit higher development influence. Furthermore, the study aims to investigate how centralized resource allocation models—enhanced by a revised returns to scale principle—can support efficient resource distribution, identify countries with the greatest improvement potential, and inform effective development strategies. The key insights gained from this research as follows:

- The application of the enhanced centralized resource allocation model has been shown in [1] to result in more accurate resource distribution among countries pursuing sustainable development goals.
- Output indicators with higher development impact coefficients significantly influence the optimal allocation of resources in centralized DEA models.
- Optimized resource allocation under this enhanced DEA framework can result in overall input savings while maintaining or increasing total outputs.

Achieving sustainable development—especially in critical areas such as energy, water, and agriculture—is one of the major global challenges, as natural resources are limited while population and national demands are continuously increasing. Under such conditions, the optimal and equitable allocation of resources plays a key role in realizing sustainable development goals. Building upon the principle of Pseudo-Returns to Scale (P-RTS) [5], which was introduced to model development processes with heterogeneous growth rates across indicators, this study's novelty lies in applying the P-RTS framework—developed from centralized resource allocation models incorporating the pseudo-returns to scale principle as proposed in [1]—to a practical regional case involving resource allocation among East Asia and Pacific countries.

2. literature Review

1.2 Energy, Environment, and Agricultural Efficiency: A Review of DEA Applications

A systematic review of the performance of renewable energies from the perspectives of efficiency and productivity was conducted in [6], where Data Envelopment Analysis (DEA) was employed and directions for future research were proposed. Similarly, national-level energy management performance was evaluated in [7], in which DEA was applied to compare indicators such as energy intensity and productivity across various countries. In the domain of agriculture and environmental assessment, DEA models were utilized in [8] to measure both energy and environmental efficiency in the agricultural sector of the European Union, adopting a multi-indicator approach to compare countries' resource utilization efficiency. Case studies in Peru were carried out in [9,10], where ecological data were used to evaluate the environmental efficiency of potato production systems by incorporating climatic and managerial variables. In [11], a hybrid model was developed to assess energy productivity in Pakistan's agricultural sector, examining both economic and technical dimensions of system efficiency. From a broader sustainability perspective, an integrated DEA–ecological footprint approach was adopted in [12] to evaluate sustainable development in Jiangsu Province, China, by analyzing environmental, economic, and social indicators within a unified analytical framework. More recently, a 2023 study evaluated the performance of G8 and SAARC countries across the three dimensions of sustainability—environmental, economic, and social—using DEA models, offering a comparative perspective between developed and developing regions. With the expanding applications of DEA, resource allocation under limited availability—aimed at optimizing overall system performance—has gained significant importance.

2.2 Centralized Resource Allocation in DEA: Models and Developments

The CRA model within the DEA framework was introduced in [4], where input resources are centrally distributed among DMUs to achieve predefined performance targets. In these models, the position of each unit relative to the efficiency frontier, as well as the optimal combination of input consumption and output production at the system level, is analyzed using multiplier-based models [13]. These approaches are commonly applied in evaluating and improving public programs and ensuring fair resource distribution.

Meanwhile, in recent decades, DEA has increasingly been used as a tool to assess the performance of countries along the path toward sustainable development.

Studies such as [14], which focus on environmental efficiency, and [15], which evaluate energy productivity in Asian countries, demonstrate DEA's significant role in analyzing both environmental and economic efficiency. These studies emphasize the necessity of multi-indicator evaluations—including natural resources, energy, and access to sustainable infrastructure—for assessing national development. Various researchers have proposed frameworks and models for centralized resource allocation and technical efficiency analysis. For example, an integrated framework was presented in [16] to analyze the relationship between centralized cost resource allocation and output distribution in firms, along with an algorithm to solve related nonlinear programming problems. This framework allows decision-makers to evaluate and compare the optimal mix of inputs and outputs across multiple units. A quantitative analysis was conducted in [17] using DEA and centralized resource allocation in flow networks, examining the relationship between production profit from resource allocation and its associated costs. Similarly, DEA-based approaches with a focus on common weights in centralized management were reviewed in [18], aiming to determine the optimal flow of resources. In the field of environmental applications, a multi-objective model was proposed in [19] for centralized resource allocation aimed at energy conservation and pollution reduction. The findings revealed that pollution reduction was more significant than the reduction in desirable energy outputs. In [20], group performance under centralized management was evaluated, and a novel method was introduced for decomposing centralized performance indicators, enabling the identification of meta frontiers.

3.2 Beyond Classical Returns to Scale: The Emergence of Pseudo-RTS (P-RTS)

However, classical models of Returns to Scale (RTS) face limitations when the development rates of indicators (inputs or outputs) are not uniform. To address this issue, the concept of P-RTS in CRA was introduced in [1]. This novel principle enables greater flexibility in modeling systems in which indicators evolve at different rates. When the development coefficients of indicators are uniform, the P-RTS framework coincides with the classical RTS; however, when the growth rates of indicators differ, P-RTS offers a more appropriate structure for analyzing development dynamics [5].

3. Methodology and Data Analysis

DEA models are typically designed based on fundamental principles, and in this study, the principle of "pseudo-returns to scale" is incorporated. This principle indicates that changes in inputs have different effects on various groups of outputs. To implement this, the indicators are categorized into two groups of outputs and one group of inputs, such that the returns to scale of the inputs are considered equal to those of the first group of outputs, while the returns to scale of the second group of outputs are assumed to be larger. This approach enables system managers to allocate resources in the most optimal way, taking into account the differing importance of outputs. The required models and frameworks are presented below based on the assumptions introduced in [1]. Model 1 has been employed to evaluate the performance of decision-making units under the principle of pseudo-returns to scale for indicators with the assumed categorizations.

$$Min \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}}{1+\frac{1}{s}\sum_{r=1}^{s}\frac{s_r^+}{y_{ro}}} \qquad (1)$$

$$\begin{aligned}
&s.t\\
&\sum_{j=1}^{n}\lambda_j x_{ij}+s_i^- = x_{io}, \quad i=1,..,m, && (c.1)\\
&\sum_{j=1}^{n}\lambda_j y_{rj}-s_r^+ = y_{ro}, \quad r=1,..,p, && (c.2)\\
&\sum_{j=1}^{n}\gamma_j y_{rj}-s_r^+ = y_{ro}, \quad r=p+1,..,s, && (c.3)\\
&\sum_{j=1}^{n}\gamma_j \ge \sum_{j=1}^{n}\lambda_j, && (c.4)\\
&\lambda_j,\gamma_j \in \Lambda,\ j=1,...,n,\ s_i^- \ge 0, i=1,...,m,\ s_r^+ \ge 0, r=1,...,s.
\end{aligned}$$

Such that, if $\Lambda = \left(\lambda_j, \gamma_j \ge 0\right)$, then model is designed under P-CRS, if $\Lambda = \left(\sum_{j=1}^{n}\lambda_j \le 1, \sum_{j=1}^{n}\gamma_j \le 1\right)$, under P-DRS and if $\Lambda = \left(\sum_{j=1}^{n}\lambda_j \ge 1, \sum_{j=1}^{n}\gamma_j \ge 1\right)$, under P-IRS is called.

Model 2 represents the developed centralized resource allocation model formulated under each of the following conditions. For each three different statuses of P-RTS,

$$\Omega\begin{cases}
1)\ \lambda_{jk},\gamma_{jk} \ge 0,\ \sum_{j=1}^{n}\gamma_{jk} \ge \sum_{j=1}^{n}\lambda_{jk}, k=1,...,n.\\
2)\sum_{j=1}^{n}\lambda_{jk} \le 1,\ \sum_{j=1}^{n}\gamma_{jk} \le 1, \sum_{j=1}^{n}\gamma_{jk} \ge \sum_{j=1}^{n}\lambda_{jk}, k=1,...,n.\\
3)\sum_{j=1}^{n}\lambda_{jk} \ge 1,\ \sum_{j=1}^{n}\gamma_{jk} \ge 1, \sum_{j=1}^{n}\gamma_{jk} \ge \sum_{j=1}^{n}\lambda_{jk}, k=1,...,n.
\end{cases}$$

The model (2), model of development CDEA is showed as follows,

$$Min\ \frac{1}{m}\sum_{i=1}^{m}\theta_i - \varepsilon\sum_{r=1}^{s}s_r^+ \qquad (2)$$

$$\begin{aligned}
&s.t\\
&\sum_{k=1}^{n}\sum_{j=1}^{n}\lambda_{jk}x_{ij} \le \theta_i\sum_{j=1}^{n}x_{ij}, \quad i=1,...,m, && (c.1)\\
&\sum_{k=1}^{n}\sum_{j=1}^{n}\lambda_{jk}y_{rj} - s_r^+ = \sum_{j=1}^{n}y_{rj}, \ r=1,...,p, && (c.2)\\
&\sum_{k=1}^{n}\sum_{j=1}^{n}\gamma_{jk}y_{rj} - s_r^+ = \sum_{j=1}^{n}y_{rj}, \ r=p+1,...,s, && (c.3)\\
&\sum_{j=1}^{n}\gamma_{jk} \ge \sum_{j=1}^{n}\lambda_{jk}, \quad k=1,...,n, && (c.4)\\
&\begin{cases}\lambda_{jk},\gamma_{jk} \in \Omega,\ j=1,...,n, k=1,...,n,\\ s_r^+ \ge 0, r=1,...,s, \theta_i \ is\ free, i=1,..,m.\end{cases}
\end{aligned}$$

In the application section, Model 1 is first applied to the data to evaluate the efficiency of the decision-making units under all three pseudo-returns to scale conditions. Then, Model 2 is applied to the data related to the 17 countries for centralized resource allocation, and subsequently, the efficiency of the targets for each decision-making unit is examined.

4. Practical Application

The study is conducted on 17 selected countries from the East Asia and Pacific region. The reason for selecting these 17 countries is the availability of more complete data for the chosen indicators related to sustainable development in the year 2015. The data were obtained from the World Bank[2] database. The indicators examined for these countries include five input indicators and three output indicators. The categorization of the indicators is performed based on the variation coefficients of the data and their interaction with policymakers. the World Bank database. The indicators examined

2 https://databank.worldbank.org/source/world-development-indicators#

for these countries include five input indicators and three output indicators. The categorization of the indicators is performed based on the variation coefficients of the data and their interaction with policymakers.

Based on the analysis of the developed returns to scale (coefficient of variation) of the input and output indicators in the DEA model, it was observed that certain inputs exhibit high variability among the countries studied. However, for the purpose of targeting in efficiency analysis, the outputs were categorized based on a comparison with inputs that have lower returns to scale, particularly the indicator of "per capita energy consumption," which demonstrates more stable behavior compared to other inputs. Accordingly, outputs that are more homogeneous in terms of returns to scale and closer to controllable inputs were grouped together (such as the indicators of "access to electricity" and "food production index"), while outputs that exhibit higher fluctuations and follow a different development trajectory (such as "share of renewable electricity") were placed in a second category. This approach not only aligns with the economic and environmental logic of East Asian countries but also makes the DEA model analysis more realistic and grounded in the structural differences among countries.

The indicators are presented in Table 1. Additionally, references to studies that have utilized these indicators are provided in Table 1.

Table 1. Indicators and References

Indexes	Authors	Type of index	Series Code
Energy use (kg of oil equivalent per capita)	[21, 22]	Input	EG.USE.PCAP.KG.OE
Agricultural land (sq. km)	[23, 24, 25]	Input	AG.LND. AGRI. K2
Fertilizer consumption (kilograms per hectare of arable land)	[21, 23, 24, 26, 27]	Input	AG.CON.FERT. ZS
Rural land area (sq. km)	[24]	Input	AG.LND.TOTL.RU.K2
Annual freshwater withdrawals, total (billion cubic meters)	[22, 24,28]	Input	ER.H2O.FWTL. K3
Food production index (2014-2016 = 100)	[25]	Output	AG.PRD.FOOD. XD
Access to electricity (% of population)	[29]	Output	EG.ELC.ACCS. ZS
Renewable electricity output (% of total electricity output)	[30]	Output	EG.ELC.RNEW. ZS

The indicators are defined in Table 2.

Table 2. Description of Indicators

Access to electricity (% of population)	Access to electricity is the percentage of population with access to electricity. Electrification data are collected from industry, national surveys and international sources.
Agricultural land (sq. km)	Agricultural land includes temporarily arable land, orchards, and permanent crops such as fruit trees and flowering shrubs. It also encompasses permanent pastures used for grazing or forage production for five or more years.
Energy use (kg of oil equivalent per capita)	Energy use refers to use of primary energy before transformation to other end-use fuels, which is equal to indigenous production plus imports and stock changes, minus exports and fuels supplied to ships and aircraft engaged in international transport.
Food production index (2014-2016 = 100)	Food production index covers food crops that are considered edible and that contain nutrients. Coffee and tea are excluded because, although edible, they have no nutritive value.
Renewable electricity output (% of total electricity output)	Renewable electricity is the share of electrity generated by renewable power plants in total electricity generated by all types of plants.
Rural land area (sq. km)	Rural land area is measured in square kilometers using urban extent grids that differentiate urban and rural areas based on population, settlement points, and Nighttime Lights. Urban areas are identified by contiguous lighted cells or settlement buffers with populations over 5,000.
Fertilizer consumption (kilograms per hectare of arable land)	Fertilizer consumption refers to the amount of nitrogen, potash, and phosphate fertilizers used per unit of arable land, excluding traditional manures. Arable land includes temporary crops, meadows, gardens, and fallow land but excludes land abandoned due to shifting cultivation.
Annual freshwater withdrawals, total (billion cubic meters)	Annual freshwater withdrawals include total water taken for agriculture, industry, and domestic use, excluding evaporation losses, and may involve desalination and nonrenewable sources. Withdrawals can exceed renewable resources due to reuse or extraction from nonrenewable aquifers.

Table 3 and Table 4 presents the data related to the five input indicators and three output indicators corresponding to 17 countries in East Asia and the Pacific, respectively.

Table 5 presents the efficiency scores of the 17 evaluated countries under different P-RTS conditions using Model 1.

Table 3. Study Data: Input Indicators

DMUs	East Asia & Pacific Countries	I1	I2	I3	I4	I5
		Energy use (kg of oil equivalent per capita)	Agricultural land (sq. km)	Fertilizer consumption (kilograms per hectare of arable land)	Rural land area (sq. km)	Annual freshwater withdrawals, total (billion cubic meters)
D1	Australia	5318.666793	3481190	79.4678592	7650418.083	9.22
D2	Brunei Darussalam	6437.002474	134	177.25	5571.881756	0.092
D3	Cambodia	379.745574	56476.28	29.66733796	176180.6789	2.184
D4	China	2172.63044	5237038	480.2420628	8723723.06	591.8
D5	Indonesia	692.3595852	578000	339.5853057	1820838.066	339.5853057
D6	Japan	3400.592711	48460	225.3269917	316736.2049	79.91742857
D7	Korea, Dem. People's Rep.	372.7980879	26300	51.37650862	119025.2203	8.6578
D8	Korea, Rep.	5239.003454	17360	337.8127893	86793.3716	29.197
D9	Lao PDR	602.3395488	23350	33.7452844	228354.3777	7.85
D10	Malaysia	2706.926963	85699.7	1896.164108	318197.5661	6.226
D11	Mongolia	1516.3411	1136644.1	17.46264297	1549425.131	0.4296
D12	Myanmar	353.4068269	127489.999	13.32071996	660979.5454	33.231
D13	Philippines	499.0707763	125270	139.4234258	282119.5821	86.4
D14	Singapore	5832.187484	6.6	143.1607143	210.1625761	0.5075
D15	Thailand	1932.67391	228460	135.2745172	491891.911	57.307
D16	Viet Nam	679.445924	121478	432.2736034	297626.6621	81.862
D17	New Zealand	4417.094574	107120	1786.005439	270548.6286	9.875
Sum	-	42552.29	11400477	6317.559	22998640	1344.342

Table 4. Study data: Output Indicators

DMUs	East Asia & Pacific Countries	O1	O2	O3
		Food production index (2014-2016 = 100)	Access to electricity (% of population)	Renewable electricity output (% of total electricity output)
D1	Australia	101.22	100	13.34208
D2	Brunei Darussalam	97.31	100	0.031190
D3	Cambodia	98.76	62.7	48.58707
D4	China	101.33	100	23.86494
D5	Indonesia	101.74	97.5	14.39443
D6	Japan	99.72	100	14.17878
D7	Korea, Dem. People's Rep.	98.49	40	52.70770

D8	Korea, Rep.	99.54	100	2.598460
D9	Lao PDR	104.55	89.7	98.18733
D10	Malaysia	100.75	99.9	11.14019
D11	Mongolia	110.54	88	4.047524
D12	Myanmar	100.99	60.5	68.08996
D13	Philippines	100.77	89.1	25.52859
D14	Singapore	99.27	100	4.179670
D15	Thailand	96.59	99.6	12.98142
D16	Viet Nam	100.72	99.3	35.39641
D17	New Zealand	101.16	100	80.46499
Sum	-	1713.45	1526.3	509.7208

Table 5. Efficiency Scores of 17 Countries Before Allocation (Model 1)

DMUs	East Asia & Pacific Countries	Efficiency under P-CRs	Efficiency under CRS	Efficiency under P-DRS	Efficiency under DRS	Efficiency under P-IRS	Efficiency under IRS
D1	Australia	0.30166	0.3057	0.3361	0.3415	0.30167	0.3057
D2	Brunei Darussalam	1	1	1	1	1	1
D3	Cambodia	1	1	1	1	1	1
D4	China	0.1308	0.2143	0.1813	0.2524	0.1308	0.2143
D5	Indonesia	0.2799	0.5413	0.3117	0.5413	0.2799	1
D6	Japan	0.3969	0.7038	0.4286	0.7038	0.3969	1
D7	Korea, Dem. People's Rep.	1	1	1	1	1	1
D8	Korea, Rep.	0.3934	0.7618	0.3979	0.7618	0.3934	1
D9	Lao PDR	1	1	1	1	1	1
D10	Malaysia	0.5319	0.7799	0.5491	0.7796	0.53195	1
D11	Mongolia	1	1	1	1	1	1
D12	Myanmar	1	1	1	1	1	1
D13	Philippines	1	1	1	1	1	1
D14	Singapore	1	1	1	1	1	1
D15	Thailand	0.3262	0.7672	0.3523	0.7672	0.3267	1
D16	Viet Nam	0.4734	0.6823	0.5007	0.6823	0.4734	0.7089
D17	New Zealand	0.3401	0.4253	0.3542	0.4765	0.3401	0.4253

Table 5 presents the performance of countries under Model 1 and the conventional DEA model assuming classical returns to scale. The results clearly indicate that, due to the higher significance of the third output indicator relative to others, Model 1 offers a more precise differentiation in the performance of countries.

Tables 6, 8, and 10 respectively show the patterns obtained corresponding to the input indicators, while Tables 7, 9, and 11 present the output values corresponding to resource consumption after allocation, obtained by solving Model 2 on the data of 17 sustainable developing countries.
Tables 6 and 7 correspond to the constant pseudo-returns to scale condition, Tables 8 and 9 correspond to the pseudo-decreasing returns to scale condition, and Tables 10 and 11 correspond to the pseudo-increasing returns to scale condition.
The last row of each table shows the total values of each indicator.
Table 6 and 7 report almost ten distinct target points obtained from the extended CRS version of Model 2, which incorporates a differentiated coefficient on the third output indicator.
Table 8 and 9 two distinct target points obtained from the extended DRS version of Model 2, which incorporates a differentiated coefficient on the third output indicator.

Table 6. Input Targets under P-CRS (Model 2)

DMUs	East Asia & Pacific Countries	I1	I2	I3	I4	I5
		Energy use (kg of oil equivalent per capita)	Agricultural land (sq. km)	Fertilizer consumption (kilograms per hectare of arable land)	Rural land area (sq. km)	Annual freshwater withdrawals, total (billion cubic meters)
D1	Australia	6.72E+02	2.60E+04	37.620161	2.55E+05	8.7513935
D2	Brunei Darussalam	6.72E+02	2.60E+04	37.620161	2.55E+05	8.7513935
D3	Cambodia	3.80E+02	5.65E+04	29.667338	1.76E+05	2.184
D4	China	6.72E+02	2.60E+04	37.620161	2.55E+05	8.7513935
D5	Indonesia	6.55E+02	2.54E+04	36.679657	2.48E+05	8.5326087
D6	Japan	6.72E+02	2.60E+04	37.620161	2.55E+05	8.7513935
D7	Korea, Dem. People's Rep.	3.97E+02	5.30E+04	29.798999	1.80E+05	2.6818713
D8	Korea, Rep.	6.72E+02	2.60E+04	37.620161	2.55E+05	8.7513935
D9	Lao PDR	6.02E+02	2.34E+04	33.745284	2.28E+05	7.85
D10	Malaysia	6.71E+02	2.60E+04	37.582541	2.54E+05	8.7426421
D11	Mongolia	5.78E+02	3.54E+04	34.992912	2.29E+05	6.6758856
D12	Myanmar	4.67E+02	4.34E+04	31.25793	1.97E+05	4.4135655
D13	Philippines	5.98E+02	2.32E+04	33.519563	2.27E+05	7.7974916
D14	Singapore	6.72E+02	2.60E+04	37.620161	2.55E+05	8.7513935
D15	Thailand	6.69E+02	2.59E+04	37.46968	2.54E+05	8.716388
D16	Viet Nam	6.67E+02	2.58E+04	37.35682	2.53E+05	8.6901338
D17	New Zealand	6.72E+02	2.60E+04	37.620161	2.55E+05	8.7513935
Sum	-	1.04E+04	5.20E+05	6.05E+02	4.03E+06	1.28E+02

Table 7. Output Targets under P-CRS (Model 2)

DMUs	East Asia & Pacific Countries	O1	O2	O3
		Food production index (2014-2016 = 100)	Access to electricity (% of population)	Renewable electricity output (% of total electricity output)
D1	Australia	1.17E+02	102	14.87412
D2	Brunei Darussalam	1.17E+02	102	14.87412
D3	Cambodia	98.76	62.7	48.58708
D4	China	1.17E+02	102	23.86495
D5	Indonesia	1.14E+02	97.5	14.39444
D6	Japan	1.17E+02	102	14.87412
D7	Korea, Dem. People's Rep.	98.49	64.6506	52.70771
D8	Korea, Rep.	1.17E+02	102	14.87412
D9	Lao PDR	1.05E+02	89.7	98.18734
D10	Malaysia	1.16E+02	99.9	11.14019
D11	Mongolia	1.11E+02	88	4.349
D12	Myanmar	1.01E+02	73.29828	68.08997
D13	Philippines	1.04E+02	89.1	25.52859
D14	Singapore	1.17E+02	102	14.87412
D15	Thailand	1.16E+02	99.6	14.81462
D16	Viet Nam	1.16E+02	99.3	35.39642
D17	New Zealand	1.17E+02	102	80.46499
Sum	-	1.89E+03	1.56E+03	5.52E+02

Table 8. Input Targets under P-DRS (Model 2)

DMUs	East Asia & Pacific Countries	I1	I2	I3	I4	I5
		Energy use (kg of oil equivalent per capita)	Agricultural land (sq. km)	Fertilizer consumption (kilograms per hectare of arable land)	Rural land area (sq. km)	Annual freshwater withdrawals, total (billion cubic meters)
D1	Australia	7.90E+02	5.24E+04	48.10295	2.66E+05	14.84392
D2	Brunei Darussalam	6.02E+02	2.34E+04	3.37E+01	2.28E+05	7.85
D3	Cambodia	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D4	China	6.02E+02	2.34E+04	3.37E+01	2.28E+05	7.85E+00
D5	Indonesia	6.02E+02	2.34E+04	3.37E+01	2.28E+05	7.85E+00
D6	Japan	6.02E+02	2.34E+04	3.37E+01	2.28E+05	7.85
D7	Korea, Dem. People's Rep.	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D8	Korea, Rep.	6.02E+02	2.34E+04	3.37E+01	2.28E+05	7.85
D9	Lao PDR	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85

D10	Malaysia	6.02E+02	2.34E+04	3.37E+01	2.28E+05	7.85
D11	Mongolia	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D12	Myanmar	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D13	Philippines	6.02E+02	2.34E+04	3.37E+01	2.28E+05	7.85
D14	Singapore	6.02E+02	2.34E+04	3.37E+01	2.28E+05	7.85
D15	Thailand	6.02E+02	2.34E+04	3.37E+01	2.28E+05	7.85
D16	Viet Nam	6.02E+02	2.34E+04	3.37E+01	2.28E+05	7.85
D17	New Zealand	6.02E+02	2.34E+04	3.37E+01	2.28E+05	7.85
Sum	-	1.04E+04	4.26E+05	5.88E+02	3.92E+06	1.40E+02

Table 9. Output Targets under P-DRS (Model 2)

DMUs	East Asia & Pacific Countries	O1	O2	O3
		Food production index (2014-2016 = 100)	Access to electricity (% of population)	Renewable electricity output (% of total electricity output)
D1	Australia	1.03E+02	91.1	31.18884
D2	Brunei Darussalam	1.05E+02	89.7	13.34208
D3	Cambodia	1.05E+02	89.7	13.34208
D4	China	1.05E+02	89.7	13.34208
D5	Indonesia	1.05E+02	89.7	13.34208
D6	Japan	1.05E+02	89.7	13.34208
D7	Korea, Dem. People's Rep.	1.05E+02	89.7	13.34208
D8	Korea, Rep.	1.05E+02	89.7	13.34208
D9	Lao PDR	1.05E+02	89.7	98.18734
D10	Malaysia	1.05E+02	89.7	13.34208
D11	Mongolia	1.05E+02	89.7	13.34208
D12	Myanmar	1.05E+02	89.7	98.18734
D13	Philippines	1.05E+02	89.7	13.34208
D14	Singapore	1.05E+02	89.7	13.34208
D15	Thailand	1.05E+02	89.7	23.86495
D16	Viet Nam	1.05E+02	89.7	98.18734
D17	New Zealand	1.05E+02	89.7	13.34208
Sum	-	1.78E+03	1.53E+03	5.10E+02

Table 10. Input Targets under P-IRS (Model 2)

DMUs	East Asia & Pacific Countries	I1	I2	I3	I4	I5
		Energy use (kg of oil equivalent per capita)	Agricultural land (sq. km)	Fertilizer consumption (kilograms per hectare of arable land)	Rural land area (sq. km)	Annual freshwater withdrawals, total (billion cubic meters)
D1	Australia	6.12E+02	2.37E+04	34.27197	2.32E+05	7.97252
D2	Brunei Darussalam	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D3	Cambodia	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D4	China	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D5	Indonesia	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D6	Japan	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D7	Korea, Dem. People's Rep.	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D8	Korea, Rep.	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D9	Lao PDR	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D10	Malaysia	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D11	Mongolia	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D12	Myanmar	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D13	Philippines	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D14	Singapore	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D15	Thailand	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D16	Viet Nam	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
D17	New Zealand	6.02E+02	2.34E+04	33.74528	2.28E+05	7.85
Sum	-	1.02E+04	3.97E+05	5.74E+02	3.89E+06	1.34E+02

Table 11. Output Targets under P-IRS (Model 2)

DMUs	East Asia & Pacific Countries	O1	O2	O3
		Food production index (2014-2016 = 100)	Access to electricity (% of population)	Renewable electricity output (% of total electricity output)
D1	Australia	1.06E+02	91.1	13.55032
D2	Brunei Darussalam	1.05E+02	89.7	13.34208
D3	Cambodia	1.05E+02	89.7	13.34208
D4	China	1.05E+02	89.7	13.34208
D5	Indonesia	1.05E+02	89.7	13.34208
D6	Japan	1.05E+02	89.7	13.34208
D7	Korea, Dem. People's Rep.	1.05E+02	89.7	13.34208
D8	Korea, Rep.	1.05E+02	89.7	13.34208
D9	Lao PDR	1.05E+02	89.7	13.34208

D10	Malaysia	1.05E+02	89.7	13.34208
D11	Mongolia	1.05E+02	89.7	13.34208
D12	Myanmar	1.05E+02	89.7	13.34208
D13	Philippines	1.05E+02	89.7	13.34208
D14	Singapore	1.05E+02	89.7	13.34208
D15	Thailand	1.05E+02	89.7	2.96E+02
D16	Viet Nam	1.05E+02	89.7	13.34208
D17	New Zealand	1.05E+02	89.7	13.34208
Sum	-	1.78E+03	1.53E+03	5.10E+02

Table 10 and 11 present two distinct target points obtained from the extended IRS version of Model 2, which incorporates a differentiated coefficient on the third output indicator. By analyzing the Centralized Resource Allocation model under the conditions of Model 2 and incorporating constraints related to the unequal development coefficients of output indicators, a revised pattern of resource distribution among countries is proposed. A comparison with the total observed data across all indicators reveals that this model enables significant resource savings while sustaining or even enhancing overall production levels. These findings highlight the effectiveness of the proposed approach in guiding efficient and equitable allocation policies, particularly in the context of sustainable development. Figure 1 illustrates the percentage of resource savings and production increase relative to the initial data, under various extended returns to scale scenarios.

Figure 1 shows that there has been an increase in production for the first output indicators, while the initial production levels have been maintained for the other output indicators. Therefore, considering the proposed target patterns for the countries under various extended returns to scale conditions, it is observed that they approach the estimated efficiency frontier, and in some cases, lie directly on the frontier. This demonstrates the strength of Model 2 and its practical relevance, particularly for real-world applications such as evaluating and allocating countries in the context of sustainable development.

Table 12 shows the efficiency scores corresponding to each target obtained under the P-RTS.

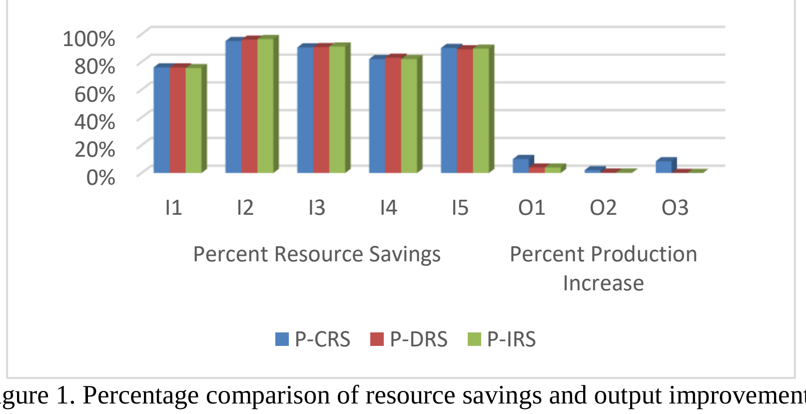

Figure 1. Percentage comparison of resource savings and output improvements

Table 12 Efficiency Scores After Resource Allocation

DMUs	East Asia & Pacific Countries	Efficiency under P-CRs	Efficiency under P-DRS	Efficiency under P-IRS
D1	Australia	1	0.6744	1
D2	Brunei Darussalam	1	1	1
D3	Cambodia	1	0.99	1
D4	China	1	1	1
D5	Indonesia	1	1	1
D6	Japan	1	1	1
D7	Korea, Dem. People's Rep.	1	0.99	1
D8	Korea, Rep.	1	1	1
D9	Lao PDR	1	0.99	1
D10	Malaysia	1	1	1
D11	Mongolia	1	0.99	1
D12	Myanmar	1	0.99	1
D13	Philippines	1	1	1
D14	Singapore	1	1	1
D15	Thailand	0.99	1	1
D16	Viet Nam	1	1	1
D17	New Zealand	1	1	1

5. Conclusion and Suggestions

In this study, the principle of Pseudo-Returns to Scale, previously introduced by [5], was employed as an effective tool for analyzing resource allocation policies in systems characterized by heterogeneous indicators—a concept that had also been applied in [1]. This approach is particularly effective in the context of sustainable development and the management of scarce resources such as energy, water, and agricultural land. The principle can guide resource allocation in an optimal manner that takes into account variations in growth rates and the relative importance of output indicators, including electricity generated from renewable sources. In practical application, the proposed model not only resulted in resource savings but also maintained or, the total production across all units experienced a slight increase under the P-CRS status Moreover, the allocated resources for each decision-making unit brought them closer to the efficient frontier of the proposed feasible production set [5], indicating an improvement in system-level efficiency.

The practical application of the proposed model in East Asian and Pacific countries demonstrated its capability to enhance decision-making processes at the regional level and facilitate balanced and sustainable development. Based on the findings of this research, the following recommendations are proposed for future studies: First, further in-depth investigations into the P-RTS principle could enhance understanding of its implications and applications across various industries, sectors, and geographical regions, thereby increasing its generalizability. Second, conducting comparative studies among countries and regions with varying resource endowments and levels of economic development would be useful to better understand how environmental and economic factors affect the effectiveness of the P-RTS model in resource allocation. Third, integrating environmental indicators into DEA models could provide a more comprehensive assessment of sustainability and the balance between economic efficiency and environmental protection. Finally, longitudinal studies to evaluate the long-term impacts of policies based on the P-RTS principle would offer valuable insights regarding the effectiveness and sustainability of this approach.

References

[1] Dehghan Chenari,S., Hosseinzadeh Lotfi, F., Farzipoor Saen, R., Rostamy Malkhalifeh, M., & Sharafi, H. (2025). Transforming Resource Allocation Strategies: Harnessing Pseudo-Returns to Scale for Optimal Performance, printed in Journal of Mathematical Extension, 18.

[2] Charnes, A., Cooper, W. W. and Rhodes, E., Measuring the efficiency of decision-making units, European Journal of Operational Research, 2(6) (1978), 429-444.

[3] Banker, R. J., Charnes, A. and Cooper, W. W., Some models for estimating technical and scale inefficiencies in data envelopment analysis, Management Science, 30(9) (1984), 1078-1092.

[4] Lozano, S., & Villa, G. (2004). Centralized resource allocation using data envelopment analysis. *Journal of Productivity Analysis*, 22(1), 143–161.

[5] Dehghan Chenari,S., Hosseinzadeh Lotfi, F., Farzipoor Saen, R., Rostamy Malkhalifeh, M., & Sharafi, H. (2025). Beyond Conventional Ratios: Introducing Pseudo-Returns to Scale in Data Envelopment Analysis. Annals of Operations Research. In press.

[6] Chachuli, F. S. M. (2020). Renewable energy performance evaluation studies using the data envelopment analysis (DEA): A systematic review. *Renewable and Sustainable Energy Reviews*, *133*, 110114.

[7] Sulukan, E., Karataş, M., & Akgün, İ. (2017). Energy management performance in country scale: A data envelopment analysis. *Renewable and Sustainable Energy Reviews*, *78*, 746–754.

[8] Vlontzos, G., Niavis, S., & Manos, B. (2014). A DEA approach for estimating the agricultural energy and environmental efficiency of EU countries. *Renewable and Sustainable Energy Reviews*, *40*, 91–96.

[9] Grados, N., Schrevens, E., & De Neve, S. (2017). Eco-efficiency of smallholder potato producers in the Peruvian Andes: A technical efficiency analysis using data envelopment analysis. *Science of the Total Environment*, *595*, 130–146.

[10] Grados, N., Schrevens, E., & De Neve, S. (2019). Integrating eco-efficiency and farmer typology to analyze sustainable intensification in Andean potato farming systems. *Science of the Total Environment*, *661*, 979–991.

[11] Abbas, A., Ahmad, S., & Aslam, M. (2020). An ensemble approach for assessment of energy efficiency of agriculture system in Pakistan. *Journal of Cleaner Production*, *256*, 120382.

[12] He, J., Wan, C., Feng, H., Ai, H., & Wang, H. (2016). An integrated data envelopment analysis and emergy-based ecological footprint methodology in evaluating sustainable development: A case study of Jiangsu Province, China. *Ecological Indicators*, *60*, 445–453.

[13] Lozano, S., & Villa, G. (2005). Centralized target setting for regional energy efficiency. *European Journal of Operational Research*, 161(1), 1–12.

[14] Zhou, P., Ang, B. W., & Poh, K. L. (2008). A survey of data envelopment analysis in energy and environmental studies. *European Journal of Operational Research*, 189(1), 1–18.

[15] Lin, B., & Du, K. (2015). Energy and carbon intensity in China's industry: A nonparametric analysis of the effects of energy policies. *Energy Economics*, 51, 366–376.

[16] Cesaroni, G., Technically and cost-efficient allocations in data envelopment analysis, Socio-Economic Planning Sciences, 70 (2020), 100734.

[17] Tao, X., Xiong, B. and An, Q., DEA-based centralized resource allocation with network flows, International Transactions in Operational Research, 0 (2020), 1-33.

[18] Afsharian, M., Ahn, H. and Harms, S. G., A review of DEA approaches applying a common set of weights: the perspective of centralized management, European Journal of Operational Research, 294 (2021), 3-15.

[19] Madadi, S., Hosseinzadeh Lotfi, F., Fallah Jelodar, M. and Rostamy-Malkhalifeh, M., Centralized resource allocation based on energy saving and environmental pollution reduction using data envelopment analysis models, Business Informatics, 16(1) (2022), 83-100.

[20] Fang, L., Measuring and decomposing group performance under centralized management, European Journal of Operational Research, 297(3) (2022), 1006-1013.

[21] Mousavi-Avval, S. H., Rafiee, S., Jafari, A., & Mohammadi, A. (2011). Optimization of energy consumption for soybean production using Data Envelopment Analysis (DEA) approach. *Applied Energy*, *88*(11), 3765-3772.

[22] Valadkhani, A., Roshdi, I., & Smyth, R. (2016). A multiplicative environmental DEA approach to measure efficiency changes in the world's major polluters. *Energy Economics*, *54*, 363-375.

[23] Li, M., Zhao, W., Tian, C., Li, Y., Feng, X., Guo, B., & Yao, Y. (2023). Moderate operation scales of agricultural land under the greenhouse and open-field production modes based on DEA model in mountainous areas of southwest China. *Heliyon, 9*(11).

[24] Egbo, O. P., Ezeaku, H. C., Okolo, V. O., Anisiuba, C. A., Ibe, G. I., Okeke, O. M., & Igwe, P. A. (2023). Enhancing agricultural and industrial productivity through freshwater withdrawals and management: implications for the BRICS countries. *Environment, Development and Sustainability*, *25*(4), 3771-3799.

[25] Abdallah, M. B., Farkas, M. F., Vasa, L., & Lakner, Z. (2023). Food Security of Tunisia: Comprehensive Analysis of a Composite Index. *Acta Polytechnica Hungarica*, *20*(10).

[26] Liu, Q., Wu, T. Y., Pu, L., & Sun, J. (2022). Comparison of fertilizer use efficiency in grain production between developing countries and developed countries. *Journal of the Science of Food and Agriculture*, *102*(6), 2404-2412.

[27] Bai, X., Wang, Y., Huo, X., Salim, R., Bloch, H., & Zhang, H. (2019). Assessing fertilizer use efficiency and its determinants for apple production in China. *Ecological Indicators*, *104*, 268-278.

[28] Lozano, S., & Borrego-Marín, M. M. (2024). A metafrontier network DEA approach for water usage efficiency assessment in the light of SDG target 6.4. *Environmental Science & Policy*, *160*, 103857.

[29] Lan, J., Khan, S. U., Sadiq, M., Chien, F., & Baloch, Z. A. (2022). Evaluating energy poverty and its effects using multi-dimensional based DEA-like mathematical composite indicator approach: Findings from Asia. *Energy Policy*, *165*, 112933.

[30] Mezősi, A., Szabó, L., & Szabó, S. (2018). Cost-efficiency benchmarking of European renewable electricity support schemes. *Renewable and Sustainable Energy Reviews*, *98*, 217-226.