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Ecological Footprint Efficiency of G7 Countries: An Integrated Slack-Based Measure Data Envelopment Analysis and ROC Analysis

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Abstract

The objectives of this study are to assess the efficiency of the ecological footprint of seven G7 countries (Canada, France, Germany, Italy, Japan, the United Kingdom and the United States), and to test the diagnostic performance of input and output variables in determining the efficiency status of the seven G7 countries. For these purposes, the study has a two-stage analysis design. In the first stage, the Input Orientation Slack-Based Data Envelopment Analysis (DEA) model was employed using three input variables (Investment by Asset, Labour Force Participation Rate and Total Energy Consumption) and two output variables (Ecological Footprint (undesirable) and Gross Domestic Product). In the second stage, ROC Analysis was conducted to assess the diagnostic performance of the input and output variables in determining the Efficiency Status of G7 countries. The dataset belongs to 2025 or the nearest year, and it is gathered from Enerdata.net, Global Footprint Network, and OECD. While the first stage of analysis design was conducted using the deaR package in the R project, the second stage was carried out using Inonu University Faculty of Medicine, Department of Biostatistics and Medical Informatics, Diagnostic Tests and ROC Analysis Software. According to the first stage of analysis design, it was determined that 4 out of 7 G7 countries are efficient (Germany, Italy, the United Kingdom and the United States), while the remaining three countries (Canada, France and Japan) were found to be inefficient. Besides, all four efficient G7 countries rank first, while Japan ranks last among the seven G7 countries. According to the second stage of analysis design, it was determined that i1: Investment by Asset input variable could distinguish the Efficiency Status with the cutoff points (21.723). Given that the ecological footprint efficiency of G7 nations has not been extensively investigated in current literature, this research is notable for utilising the Slack-Based Measure Data Envelopment Analysis and ROC Analysis to address this knowledge gap.

Keywords: Data Envelopment Analysis, ROC Analysis, Ecological Footprint, G7 Countries

1. INTRODUCTION

United Nations Sustainable Development Goal-7 (SDG 7) aims to ensure access to affordable, reliable, sustainable and modern energy for all (United Nations Department of Economic and Social Affairs Sustainable Development, 2021). In achieving SDG 7, it is imperative to acknowledge that upgrading renewable energy performance is fraught with uncertainty (J. Li et al., 2024). Environmental efficiency plays a crucial role in achieving SDG 7 (Mamghaderi et al., 2023).

Environmental sustainability refers to the combination of several perspectives, procedures, and paths to accomplish that goal, such as growing crops, self-sustaining agriculture and food, well-structured governance, technological developments, use of recyclable materials as well as renewable fuels, construction of additional communities inside a previously rural region without demolishing the ecosystems or causing environmental harm and so forth (Saif-Alyousfi & Alshammari, 2025).

Since understanding the impact of environmental sustainability practices is a complex task due to the multifaceted nature of sustainability itself, impact assessments must consider ecological, economic, and social dimensions, as well as long-term and short-term effects (Tennakoon et al., 2024).

Ecological footprint is the representation of environmental sustainability, and it is a comprehensive concept that assesses forests, water, clean air, grazing, and farming areas (Zhao et al., 2024). Many human activities place demands on the planet’s capacity, including the provision and processing of food, the construction and maintenance of housing, transportation, and the consumption of goods and services (Wackernagel & Kitzes, 2008). Ecological footprint measures the amount of area, that is, land or sea, which is required to absorb the waste generated through human activities or to support the production of resources consumed by populations, and includes six dimensions: cropland, forestland, carbon, fishing grounds, grazing land, and built-up area (Akpanke et al., 2024).

Data Envelopment Analysis (DEA) method is behind linear mathematical programming, which is a decision-making tool used to measure the relative production efficiency between decision-making units (DMUs), estimate production boundaries, and evaluate the efficiency of DMUs, and can also be used to evaluate the efficiency analysis of multiple inputs and outputs in a decision unit (Hsu et al., 2023).

One way to assess the accuracy of a decision-making process is to compare the organisation's decision to the option that would optimise its benefits (Wang, 2014). In addition to being frequently used in medical decision-making, Receiver Operating Characteristic (ROC) graphs—a curve that plots a diagnostic test's sensitivity against its false positive rate across all possible threshold values for defining positivity—have also become more and more popular in business optimisation analysis, health policy making, clinical studies, and health economics in recent years (Fawcett, 2006; Kampfrath & Levinson, 2013; Wang, 2014). It is a tool for evaluating an instrument's performance (e.g. G. As part of a measurement system used for classification in an entity test, "true positive rates" (TPR, sensitivity) are plotted against decision risks like "false positive rates" (FPR, fall-out) using a testing device or machine-learning algorithm (Pendrill et al., 2023).

Therefore, the G7 economies include economically developed countries on a global scale; the high economic complexity and ecological behaviour of these countries have led to increased concern in other countries within the context (Balsalobre-Lorente et al., 2024). The ecological footprint is one way of measuring sustainability on a country level (Khaddour et al., 2024).

In this context, the study has two objectives: (i) to assess the efficiency of the ecological footprint of seven G7 countries *(Canada, France, Germany, Italy, Japan, the United Kingdom and the United States)*, (ii) to test the diagnostic performance of input and output variables in determining the efficiency status of the seven G7 countries. For these purposes, the study has a two-stage analysis design. In the first stage; Input Orientation Slack-Based DEA model (SBM-DEA) was conducted using three input variables (Investment by Asset, Labour Force Participation Rate and Total Energy Consumption) and two output variables (Ecological Footprint (undesirable) and Gross Domestic Product). In the second stage, ROC Analysis was conducted to assess the diagnostic performance of the input and output variables in determining the Efficiency Status of G7 countries.

2. CONCEPTUAL FRAMEWORK

This one, which also employs the Slack-Based Measure, is particularly valuable because it fills a research gap on the efficiency of the environmental footprints of the G7 nations, even if there are some studies on the relevant fields.

Since determining the relationship between the G7 countries' ecological footprint and natural resources is crucial (Zhao et al., 2024); an important instrument within these countries' environmental management is the measurement of ecological efficiency (Dyckhoff & Allen, 2001) , and Data Envelopment Analysis (DEA) can be regarded as a measuring tool of productivity in several research fields, including environmental, business, healthcare, public administration, etc. (Charles & Kumar, 2012; Emrouznejad & Cabanda, 2014; Gregoriou & Zhu, 2005). Table 1 lists some studies that used Data Envelopment Analysis in the area of ecological efficiency.

Table 1. Literature Summary

Title	**Author(s)**	**Input(s)**	**Output(s)**	**DMUs**	**Analysis Procedure**
Assessing the environmental efficiency of OECD countries through the lens of ecological footprint indices	(Mamghaderi et al., 2023)	- Net Capital Stock - Labour Force - Energy Consumption	-Ecological Footprint (Undesirable) -GDP	27 OEC Countries	SBM-DEA
Comprehensive Environmental Assessment Index of Ecological Footprint	(Khezri et al., 2023)	- Energy Consumption - Labour Force - Capital Stock	-GDP -Ecological Footprint (Undesirable)	27 OEC Countries	SBM-DEA
Evaluating Greenhouse Gas Emission Reduction Efficiency of OECD Countries Using Two-Stage Data Envelopment Analysis	(Hsu et al., 2023)	- Population - Labour Force - Gasoline Consumption -Coal Consumption - Electricity Consumption	- CO_2 Emission -GHG Emission	38 OECD Countries	Two-Stage DEA
Evaluation of National Environmental Efficiency Under Uncertainty Using Data Envelopment Analysis	(Grigoroudis & Petridis, 2019)	-Labour force -Population -Gross Capital Formation -Primary Energy Supply Production	-Gross Domestic Product -CO_2 Emissions (Undesirable) - SO_2 Emissions (Undesirable) -NO_2 Emissions (Undesirable)	108 Countries	SBM-DEA
Environmental performance in OECD countries: A non-radial DEA approach	(Gavurova et al., 2018)	- Primary Energy Consumption	-GDP -CO_2 (Undesirable) -SO_X (Undesirable) NO_X (Undesirable)	22 OECD Countries	SBM-DEA

Evaluating and Analyzing Renewable Energy Performance in OECD Countries Under Uncertainty: A Robust DEA Approach with Common Weights	(J. Li et al., 2024)	-Gross Fixed Capital Formation -Labour Force Primary Energy Supply	-GDP -Renewable Energy Consumption -CO_2 Emissions (Undesirable) -Municipal Waste (Undesirable)	38 OECD Countries	Robust DEA and CCR DEA
An Evaluation of Selected Environmental Indicators by Using Data Envelopment Analysis (DEA): OECD Performance Review	(Özkan & Özcan, 2018)	-Urban Population -Energy Usage Per Capita -Forest Land Percentage -Environmental Expenditure Development Ratios within the Total Budget -Total Greenhouse Gas Emissions as a Percentage of GDP -Fossil Fuel R&D Budget Ratio within the Total Public Energy Budget	-Per Capita Greenhouse Gas Emissions -Respirable Particulate Matter Concentration Relieving Percentage of the Average Population -Per Capita CO_2 Emission Rate from Transportation	34 OECD Countries	Input-Oriented CCR-DEA

According to Table 1, SBM-DEA is used to evaluate the efficiency of G7 countries in relation to the ecological footprint, and ROC Analysis is used to test the diagnostic performance of input and output variables in determining the efficiency status of G7 countries. The analysis's three input variables and two output variables are explained in detail in the sections that follow.

3. METHODOLOGY

3.1. Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a nonparametric technique for evaluating and contrasting the efficiency of decision-making units (DMUs), which include businesses, governments, and nations, and share input and output factors (Ray, 2004; Tone, 2017).

There are two types of models in data envelopment analysis (DEA): radial and nonradial (Tone, 2017).

The most basic Radial DEA model is the Constant Returns to Scale (CRS), also known as the CCR (Charnes-Cooper-Rhodes) model, and it was initially introduced by Charnes et al. in 1978 (Charnes et al., 1978). The CCR (CRS) model does this by estimating the number of inefficiencies, identifying their sources, and producing an objective evaluation of overall efficiency (Charnes et al., 1994).

Variable Returns to Scale (VRS), also referred to as the BCC (Banker-Charnes-Cooper) model, was subsequently created by Banker et al in 1984 as a representative extension of Radial DEA(Banker et al., 1984). The BCC (VRS) model estimates pure technical efficiency and identifies potential increasing, decreasing, or constant returns to scale to differentiate between technical and scale inefficiencies (Charnes et al., 1994). Whereas the CCR efficiency scores are regarded as technical efficiency, the BCC efficiency scores are regarded as pure technical efficiency (Ozcan, 2014).

Output-oriented DEA seeks to maximise output production, subject to the specified resource level, whereas input-oriented DEA seeks to produce the observed outputs with the fewest inputs (Ramanathan, 2003).

Efficiency scores of one point are considered efficient in both models; those between zero and one point are considered inefficient in input-oriented models, and those greater than one are considered inefficient in output-oriented models (Ozcan, 2014).

Proposed by (Tone, 2001) SBM-DEA, as a Non-Radial DEA, is able to deal directly with the input excesses and the output shortfalls of the DMU under evaluation, since it satisfies the properties Units Invariant, Monotone, and Reference-Set Dependent, which are not satisfied by CCR and BCC models.

The fractional programming formulas of CCR-Input Orientation (1), CCR-Output Orientation (2), BCC- Input Orientation (3), BCC- Output Orientation (4), SBM-CRS-Input Orientation (5), SBM-CRS-Output Orientation (6), SBM-VRS-Input Orientation (7) and SBM-VRS-Output Orientation (8) are as follows (Emrouznejad & Cabanda, 2014; Ozcan, 2009, 2014; Tone, 2001, 2017);

$$
\begin{aligned}
& Eff = \min_{u_r v_i} \sum_{\mathrm{i}} V_{\mathrm{i}} \, X_{\mathrm{i}J_0} \\
& \text{s.t.} \\
& \sum_r u_r y_{rj} - \sum_i v_i x_{ij} \leq 0 \quad ; \forall j \\
& \sum_r u_r y_{rj_0} = 1 \\
& u_r, v_i \geq 0 \quad ; \forall r, \forall i.
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
& Eff = \max_{u_r v_i} \sum_r u_r y_{rj_0} \\
& \text{s.t.} \\
& \sum_r u_r y_{rj} - \sum_i v_i x_{ij} \leq 0 \quad ; \forall j \\
& \sum_i v_i x_{ij_0} = 1 \\
& u_r, v_i \geq 0 \quad ; \forall r, \forall i.
\end{aligned}
\tag{2}
$$

$$
\begin{aligned}
& \min_{\lambda, \emptyset, S_i^-, S_r^+} \emptyset \\
& \text{s.t.} \\
& \sum_j \lambda_j x_{ij} + S_i^- = \emptyset_{x_{ij_0}} \quad \forall i \\
& \sum_j \lambda_j y_{rj} - S_r^+ = y_{rj_0} \quad \forall r \\
& \sum_j \lambda_j = 1 \\
& s_i^-, s_i^+ \geq 0 \quad \forall i, \forall r \\
& \lambda_j \geq 0 \quad \forall_j.
\end{aligned}
\tag{3}
$$

$$\max_{\lambda,\emptyset,S_i^-,S_r^+} \theta$$
$$\text{s.t.}$$
$$\sum_j \lambda_j x_{ij} + S_i^- = x_{ij_0} \ \forall i$$
$$\sum_j \lambda_j y_{rj} - S_r^+ = \theta y_{rj_0} \ \forall r$$
$$\sum_j \lambda_j = 1$$
$$s_i^-, s_i^+ \geq 0 \quad \forall i, \forall r$$
$$\lambda_j \geq 0 \quad \forall_j.$$

(4)

$$\rho_{\mathrm{I}}^* = \min_{\boldsymbol{\lambda},\mathbf{s}^-,\mathbf{s}^+} 1 - \frac{1}{m}\sum\nolimits_{i=1}^{m} \frac{s_i^-}{x_{ih}}$$
subject to
$$x_{ih} = \sum\nolimits_{j=1}^{n} x_{ij}\lambda_j + s_i^- \ \ (i = 1, \ldots, m)$$
$$y_{rh} = \sum\nolimits_{j=1}^{n} y_{rj}\lambda_j - s_r^+ \ \ (r = 1, \ldots, s)$$
$$\lambda_j \geq 0 \ (\forall j), \ s_i^- \geq 0 (\forall i), \ s_r^+ \geq 0 (\forall r)$$

(5)

$$1/\rho_{\mathrm{O}}^* = \max_{\boldsymbol{\lambda},\mathbf{s}^-,\mathbf{s}^+} 1 + \frac{1}{s}\sum\nolimits_{r=1}^{s} \frac{s_r^+}{y_{rh}}$$
subject to
$$x_{ih} = \sum\nolimits_{j=1}^{n} x_{ij}\lambda_j + s_i^- \ \ (i = 1, \ldots, m)$$
$$y_{rh} = \sum\nolimits_{j=1}^{n} y_{rj}\lambda_j - s_r^+ \ \ (r = 1, \ldots, s)$$
$$\lambda_j \geq 0 \ (\forall j), \ s_i^- \geq 0 \ (\forall i), \ s_r^+ \geq 0 \ (\forall r)$$

(6)

$$\rho_{\mathrm{I}}^* = \min_{\boldsymbol{\lambda},\mathbf{s}^-,\mathbf{s}^+} 1 - \frac{1}{m}\sum\nolimits_{i=1}^{m} \frac{s_i^-}{x_{ih}}$$
subject to
$$x_{ih} = \sum\nolimits_{j=1}^{n} x_{ij}\lambda_j + s_i^- \ \ (i = 1, \ldots, m)$$
$$y_{rh} = \sum\nolimits_{j=1}^{n} y_{rj}\lambda_j - s_r^+ \ \ (r = 1, \ldots, s)$$
$$\sum\nolimits_{j=1}^{n} \lambda_j = 1, \ \lambda_j \geq 0 \ (\forall j), \ s_i^- \geq 0 \ (\forall i), \ s_r^+ \geq 0 \ (\forall r)$$

(7)

$$\rho_{\mathrm{I}}^* = \min_{\boldsymbol{\lambda},\mathbf{s}^-,\mathbf{s}^+} 1 - \frac{1}{m}\sum\nolimits_{i=1}^{m} \frac{s_i^-}{x_{ih}}$$
subject to
$$x_{ih} = \sum\nolimits_{j=1}^{n} x_{ij}\lambda_j + s_i^- \ \ (i = 1, \ldots, m)$$
$$y_{rh} = \sum\nolimits_{j=1}^{n} y_{rj}\lambda_j - s_r^+ \ \ (r = 1, \ldots, s)$$
$$\sum\nolimits_{j=1}^{n} \lambda_j = 1, \ \lambda_j \geq 0 \ (\forall j), \ s_i^- \geq 0 \ (\forall i), \ s_r^+ \geq 0 \ (\forall r)$$

(8)

3.2. ROC Analysis

ROC analysis was first used during World War II to assist radar operators in distinguishing whether a blip on the radar indicated a solid object or just noise, and later, this method was utilised in diagnostic statistical research (Roumeliotis et al., 2024). The ROC curve serves as an essential method for exploring the balance between sensitivity and specificity at various thresholds for classifier outcomes (Tec, 2025). A technique for visualising, categorising, and selecting classifiers based on their effectiveness is known as a receiver operating characteristic (ROC) graph (Fawcett, 2006).

The Area Under the Curve (AUC) values are a frequently used statistic that summarises an index test's diagnostic performance, and Table 2 shows the classification table of AUC values along with their usefulness (Çorbacıoğlu & Aksel, 2023).

Table 2. Area Under the Curve Values and Their Interpretation (Çorbacıoğlu & Aksel, 2023).

AUC Value	Interpretation Suggestion
0.9 ≤ AUC	Excellent
0.8 ≤ AUC < 0.9	Considerable
0.7 ≤ AUC < 0.8	Fair
0.6 ≤ AUC < 0.7	Poor
0.5 ≤ AUC < 0.6	Fail

The Confidence Interval (CI) of 0 to 100 per cent is another commonly used scale. A CI of 0 makes the observer certain that the disease of interest is not present, while a CI of 100 makes the observer convinced that the disease of interest is there (Obuchowski, 2005). Since sample data are not fixed values and are susceptible to statistical mistakes, the AUC is often displayed alongside a 95% CI, which provides a range of possible values surrounding the actual value (Nahm, 2022).

Specificity, also known as the true negative fraction (TNF), describes the likelihood that someone who is not sick will have a negative test result, and the resulting sensitivity and specificity are both 100%, whereas sensitivity, also referred to as the true positive fraction (TPF), describes the proportion of sick patients who actually have a positive test result (Van Erkel & Pattynama, 1998).

It is crucial to establish a cut-off value with the right amount of sensitivity and specificity because lowering the standards to raise sensitivity leads to a trade-off where specificity falls (Nahm, 2022). ROC analysis enables the evaluation of many cut-off points by establishing the sensitivity and specificity of each one (He et al., 2025).

The Youden index, which is calculated as sensitivity + specificity – 1, determines the threshold value that maximises both sensitivity and specificity and aids in selecting a threshold where both metrics achieve their maximum (Çorbacıoğlu & Aksel, 2023). When moving the 45° diagonal, which is a straight line with a slope of 1, in the (0, 1) direction, Youden's J statistic is the distance between the diagonal and the ROC curve (Nahm, 2022). The optimal cut-off value was established using the Youden index test, which finds the threshold value that corresponds to the curve's point closest to the upper left corner (100 per cent sensitivity and 100 per cent specificity) (Roumeliotis et al., 2024).

3.3. The Sample and Dataset

The G7 (the United States, the United Kingdom, Germany, France, Japan, Italy, and Canada) collectively play the world leadership role (K.-W. Li, 2017). Decision Making Units (DMUs) are such units that utilize same inputs to produce the same outputs (Cooper et al., 2006).

The sample of the study consists of seven G7 countries and is presented in Table 1.

Since the sample of the study consists of all G7 countries, the following three conditions related to the homogeneous group of DMUs are met (Golany & Roll, 1989);

- The DMUs in evaluation have similar goals and carry out the same tasks,
- Every DMU operates in the similiar set of market circumstances,
- All of the DMUs in the group have similar inputs and outputs for describing their performance.

Efficiency evaluation depends on how the feasible set of input–output bundles is specified (Ray, 2004). There are three input variables and two output variables as the primary variable framework. Inputs are i1: Investment by Asset, i2: Labour Force Participation Rate and i3: Total Energy Consumption. Output is o1: Ecological Footprint (undesirable output) and o2: Gross Domestic Product.

The inputs and outputs are in line (Gavurova et al., 2018; Grigoroudis & Petridis, 2019; Hsu et al., 2023; Khezri et al., 2023; J. Li et al., 2024; Mamghaderi et al., 2023; Özkan & Özcan, 2018), as depicted in Table 2.

The dataset, which belongs to 2025 or the nearest year, is shown in Table 3 and was gathered from (Enerdata.net, 2026; Global Footprint Network, 2026; OECD, 2026).

The number of DMUs is expected to be larger than the product of the number of inputs and outputs (Ramanathan, 2003). Since there are five variables in all—three input variables and two output variables—to evaluate the efficiency of the seven G7 countries in this study, this requirement is satisfied.

Table 3. The Dataset

DMU Name	Inputs			Output	
	i1	**i2**	**i3**	**o1(ud)**	**o2**
Canada	22.910160	79.820000	302.000000	8.105368	65,441.307967
France	22.096847	74.532000	218.000000	4.770337	62,524.223344
Germany	20.460317	80.226000	242.000000	4.176634	73,956.620229
Italy	22.152328	66.607000	134.000000	4.396695	62,219.871146
Japan	26.084090	81.525000	386.000000	4.036034	52,129.995115
United Kingdom	18.670312	78.465000	145.000000	3.809503	62,872.450290
United States	21.349834	74.923000	2,180.000000	7.477144	86,116.863206
Min	*18.670312*	*66.607000*	*134.000000*	*3.809503*	*52,129.995115*
Max	*26.084090*	*81.525000*	*2,180.000000*	*8.105368*	*86,116.863206*
Mean	*21.960555*	*76.585429*	*515.285714*	*5.253102*	*66,465.904471*
Median	*22.096847*	*78.465000*	*242.000000*	*4.396695*	*62,872.450290*

According to Table 3;

- ***i1: Investment by Asset*** refers to gross fixed capital formation broken down by the type of fixed assets acquired within the economy, and relevant data is gathered from the OECD Data (OECD, 2026).

- ***i2: Labour Force Participation Rate*** is the ratio of the total labour force divided by the total working-age population, and relevant data is gathered from the OECD Data (OECD, 2026).
- ***i3: Total Energy Consumption*** includes coal, gas, oil, electricity, heat, biomass, etc. and is measured in Million Tonnes of Oil Equivalent (MTOE), and relevant data is gathered from the World Energy & Climate Statistics – Yearbook 2025 (Enerdata.net, 2026).
- ***o1: Ecological Footprint (undesirable output) i***s a measurement that calculates the extent of biologically productive land and water required by a person, group, or activity to produce all the resources it consumes and to handle the waste produced, using existing technology and resource management practices, and it is usually represented in global hectares (GHA) per individual, and relevant data is gathered from the Global Footprint Network Data (Global Footprint Network, 2026).
- ***o2: Gross Domestic Product*** is the common metric for the value added generated from the production of goods and services within a country over a specific timeframe, typically represented in US dollars as well as in US dollars per capita (current PPPs), and relevant data is gathered from the OECD Data (OECD, 2026).

3.4. Analysis Design

The study has a two-stage analysis design. In the first stage, the Input Orientation SBM-DEA model was employed using three input variables *(Investment by Asset, Labour Force Participation Rate and Total Energy Consumption)* and two output variables *(Ecological Footprint (undesirable output) and Gross Domestic Product)*. In the second stage, ROC Analysis was conducted to assess the diagnostic performance of the input and output variables in determining the Efficiency Status of G7 countries.

During the SBM-DEA Stage;

- Because inputs are more under the managers' control than outputs in the DMUs (Ozcan, 2014), SBM- DEA directly addresses both input excess and output deficiency (Tone, 2001). The Input-Oriented SBM-DEA model was used in this study.
- Every inefficient DMU was given a reference set to help it become more efficient, and options for improvement (lowering inputs or raising outputs) were computed.
- The R project's deaR package was used (Coll-Serrano et al., 2018).

During the ROC Analysis Stage;

- ROC analysis was used for evaluating for evaluating the accuracy of the DEA, which classifies G7 countries into 1 of 2 categories: efficient or inefficient (Zou et al., 2007).
- The AUC value was used for evaluating the test's ability to distinguish between efficient and inefficient G7 countries (Çorbacıoğlu & Aksel, 2023).
- For any test to be statistically significant, the lower 95% CI value of the AUC must be >0.5 (Nahm, 2022).
- The optimal cut-off value for the test that maximises sensitivity and specificity was identified (Roumeliotis et al., 2024).
- The Youden index was used to identify the optimal cutoff value (Çorbacıoğlu & Aksel, 2023).
- ROC Analysis was performed using the Inonu University Faculty of Medicine, Department of Biostatistics and Medical Informatics, Diagnostic Tests and ROC Analysis Software (Yaşar et al., 2025).

4. RESULTS

4.1. The Results of the DEA Stage

Table 4 displays the DMUs' efficiency scores, slacks (input excesses and output shortfalls), and ranking based on efficiency scores.

Table 4. Efficiency Score, Ranking, and Slacks of DMUs

DMU	Efficiency Score	Efficiency Status	Rank	s_1^-	s_2^-	s_3^-	s_1^-	s_2^+
Canada	0.789937	Inefficient	6	21.687914	70.345066	163.643232	4.336294	65,441.307967
France	0.842174	Inefficient	5	22.096847	66.998186	136.817718	4.389019	62,524.223344
Germany	1.000000	**Efficient**	1	20.460317	80.226000	242.000000	4.176634	73,956.620229
Italy	1.000000	**Efficient**	1	22.152328	66.607000	134.000000	4.396695	62,219.871146
Japan	0.679426	Inefficient	7	20.013629	73.890338	140.756343	4.036034	62,620.693760
United Kingdom	1.000000	**Efficient**	1	18.670312	78.465000	145.000000	3.809503	62,872.450290
United States	1.000000	**Efficient**	1	21.349834	74.923000	2,180.000000	7.477144	86,116.863206

Table 4 shows that four DMUs *(Germany, Italy, the United Kingdom, and the United States)* achieve a score of 1, indicating their relative efficiency by eliminating input surpluses and increasing output deficiencies. Moreover, all four effective DMUs placed first, whereas Japan was positioned last among the ten DMUs. Furthermore, Table 4 gives each DMU the input and output slack it needs to eliminate excess inputs and supplement outputs in order to reach efficiency status.

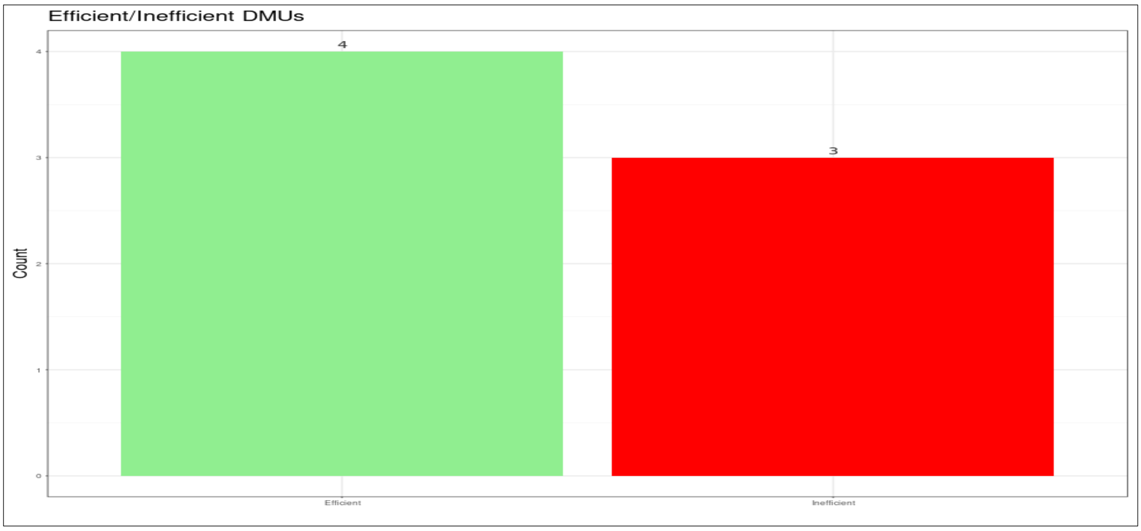

Figure 1. Efficiency Distribution

Figure 1 shows that three of the seven DMUs are inefficient (red column) and four are efficient (yellow column).

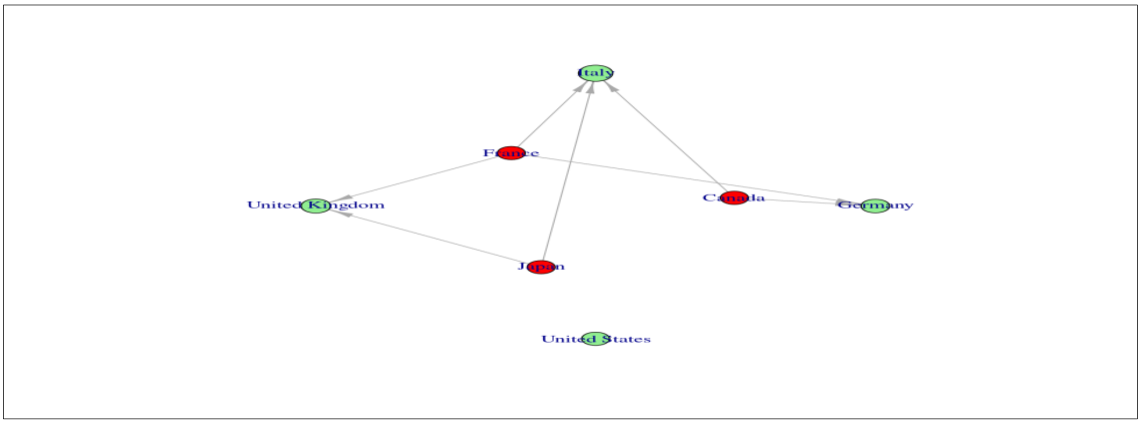

Figure 2. Network Graph

Figure 2 presents Reference Sets established to enable the three inefficient DMUs to achieve efficiency. The green circles in Figure 2 represent the efficient DMUs, while the red circles represent the inefficient ones.

Table 5 demonstrates the reference set weights, also known as Lambda -λ- values, which define the components of other producers used to construct the virtual producer (Anderson, 2003), of the Reference Set so that the two inefficient DMUs can become efficient.

Table 5. References Set of Inefficient States (λ)

DMU	Germany (λ)	Italy (λ)	United Kingdom (λ)
Canada	0.2745	0.7255	0.0000
France	0.0257	0.9708	0.0034
Japan	0.0000	0.3858	0.6142

According to Table 5;

The reference set of,

- Canada consists of Germany (λ=0.2745) and Italy (λ=0.7255).
- France consists of Germany (λ=0.0257), Italy (λ=0.9708) and the United Kingdom (λ=0.0034).
- Japan consists of Italy (λ=0.3858) and the United Kingdom (λ=0.6142).

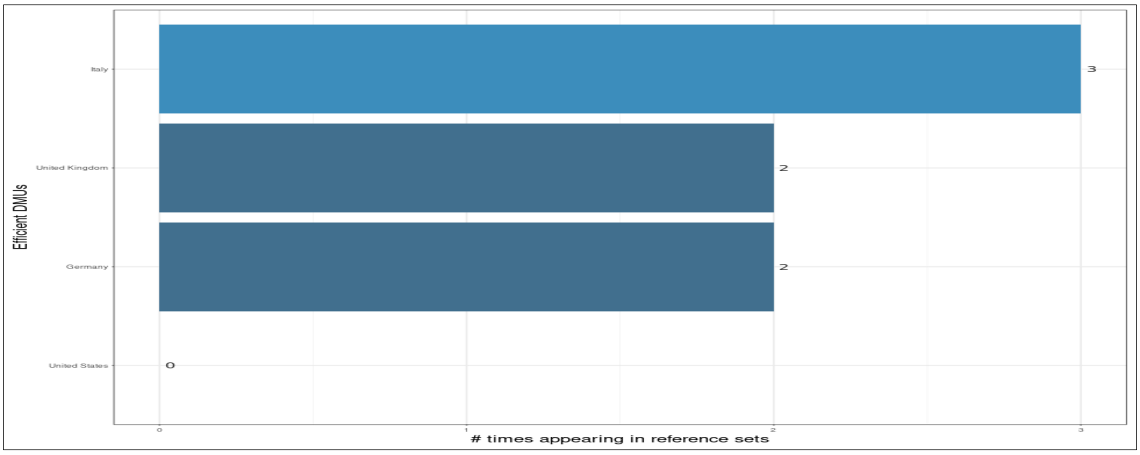

Figure 3. Reference (Peer) Counts

According to Figure-3, Italy are the most appeared DMU in the reference sets with three peer counts. Besides, although the United States is efficient, it does not appear in the reference sets.

Improvement options (reducing the inputs or increasing the outputs) for inefficient DMUs are shown in Table 6.

Table 6. Improvement Options for Inefficient Decision-Making Units (DMUs)

DMU	i*1	i*2	i*3	o*1	o*2
Canada	-1.222245	*-9.474934*	-138.356768	*-3.769074*	0.000000
France	0.000000	-7.533814	-81.182282	-0.381319	0.000000
Japan	*-6.070462*	-7.634662	*-245.243657*	0.000000	*10,490.698645*

According to Table 6;

- DMU that needs the most improvement in terms of ***i1: Investment by Asset*** is ***Japan*** with i*1 *(-1.222245)*.
- DMU country that needs the most improvement in terms of ***i2: Labour Force Participation Rate*** is ***Canada*** with i*2 *(-9.474934)*
- DMU country that needs the most improvement in terms of ***i3: Total Energy Consumption*** is ***Japan*** with i*3 *(-245.243657)*.
- DMU country that needs the most improvement in terms of ***o1: Ecological Footprint (undesirable output)*** is ***Canada*** with o*1 *(-3.769074)*.
- DMU country that needs the most improvement in terms of ***o2: Gross Domestic Product*** is ***Japan*** with o*1 *(10,490.698645)*.

4.2. The Results of the ROC Analysis Stage

The results of the ROC Analysis for the diagnostic performance of the input and output variables in determining the Efficiency Status of DMUs are presented in Table 7.

Table 7. Diagnostic Performance in Determining the Efficiency Status of Input and Output Variables

Variables	Groups	Median (IQR)	AUC (%95 CI)	Z- Test	p	Youden Index	Cut- off Value	Sensitivity (%)	Specificity (%)
i1: Investment by Asset	Efficient	20.9051 (1.5376)	0.917 (0.686-1)	3.536	**<0.001**	0.75	21.723	1	0.75
	Inefficient	22.9102 (1.9936)							
i2: Labour Force Participation Rate	Efficient	76.694 (6.0613)	0.667 (0.159-1)	0.643	0.52	0.417	79.142	0.667	0.75
	Inefficient	79.82 (3.4965)							
i3: Total Energy Consumption	Efficient	193.5 (584.25)	0.667 (0.177-1)	0.667	0.505	0.5	181.5	1	0.5
	Inefficient	302(84)							
o1: Ecological Footprint	Efficient	4.2867 (1.082)	0.667 (0.159-1)	0.643	0.52	0.417	4.584	0.667	0.75
	Inefficient	4.7703 (2.0347)							
o2: Gross Domestic Product	Efficient	68414.5353 (14287.3755	0.75 (0.328-1)	1.162	0.245	0.5	6,9698.964	1	0.5
	Inefficient	62524.2233 (6655.6564)							

AUC; Area Under Curve, CI; Confidence Interval

According to Table 7;

It was determined that the *i1: Investment by Asset* input variable *(AUC=0.917 [95%CI: (0.686-1)]; p<0.001; Figure 4.)* could distinguish the Efficiency Status. In this input variable, sensitivity *(1)* and specificity *(0.75)* were calculated for the cutoff point *(21.723)* determined by the Youden index *(0.75)*.

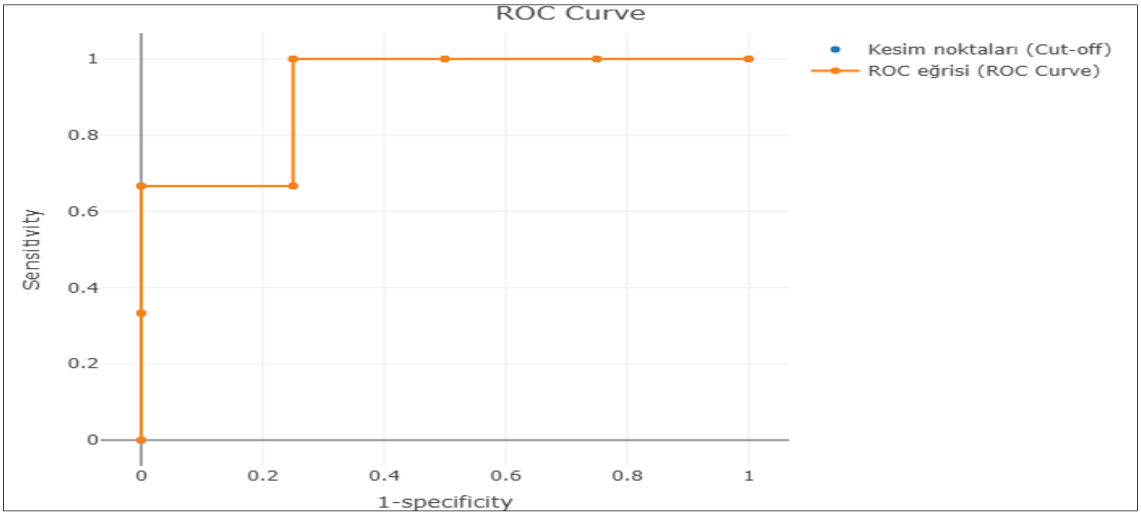

Figure 4. ROC Curve in Determining the Efficiency Status (for i1: Investment by Asset Input Variable)

Sensitivity *(0.667)* and specificity *(0.75)* were found for the cutoff point *(79.142)* determined by the Youden index *(0.417)* in the *i2: Labour Force Participation Rate* input variable. However, this input variable was not identified as the diagnostic factor in determining Efficiency Status *(p=0.52; Figure 5)*.

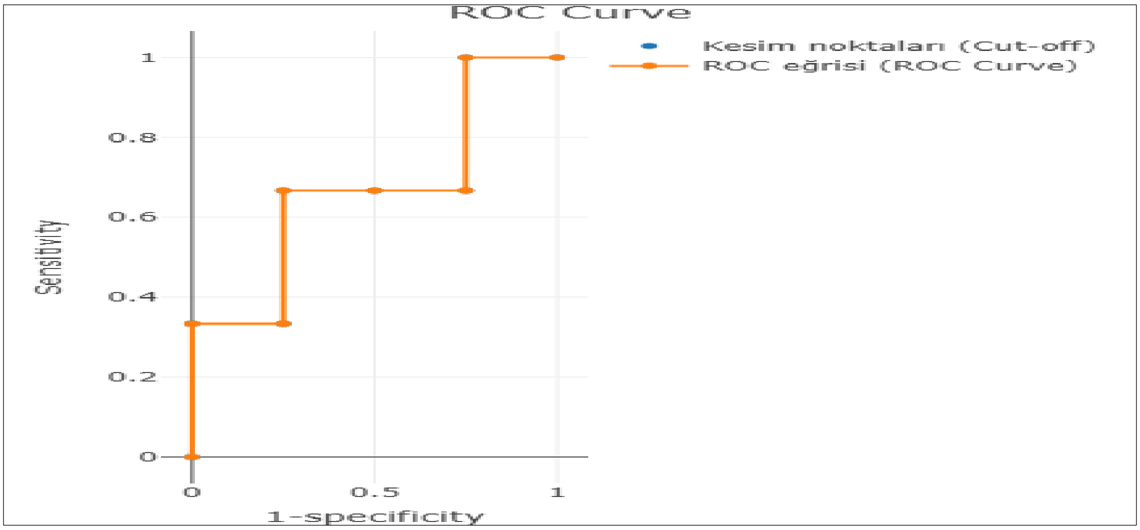

Figure 5. ROC Curve in Determining the Efficiency Status (for i2: Labour Force Participation Rate Input Variable)

Sensitivity *(1)* and specificity *(0.5)* were found for the cutoff point *(181.5)* determined by the Youden index *(0.5)* in the *i3: Total Energy Consumption* input variable. However, this input variable was not identified as the diagnostic factor in determining Efficiency Status *(p=0.505; Figure 6)*.

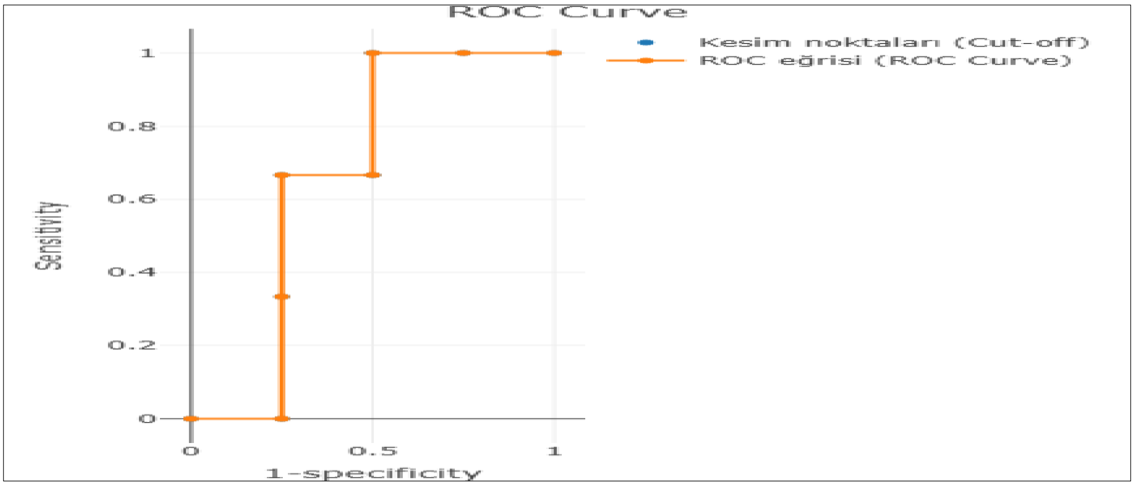

Figure 6. ROC Curve in Determining the Efficiency Status (for i3: Total Energy Consumption Input Variable)

Sensitivity *(0.667)* and specificity *(0.75)* were found for the cutoff point *(4.584)* determined by the Youden index *(0.417)* in the *o1: Ecological Footprint* input variable. However, this output variable was not identified as the diagnostic factor in determining Efficiency Status *(p=0.52; Figure 7).*

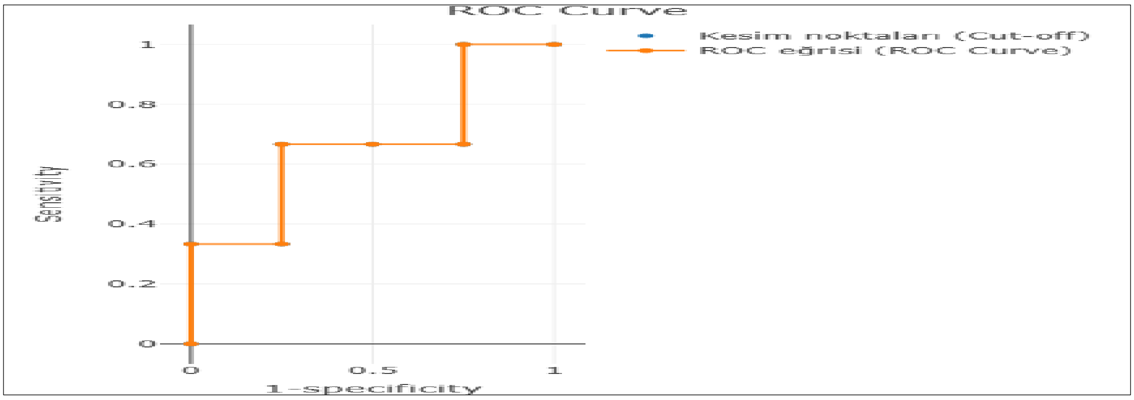

Figure 7. ROC Curve in Determining the Efficiency Status (for o1: Ecological Footprint Output Variable)

Sensitivity *(1)* and specificity *(0.5)* were found for the cutoff point *(69,698.964)* determined by the Youden index *(0.5)* in the *o2: Gross Domestic Product* input variable. However, this output variable was not identified as the diagnostic factor in determining Efficiency Status *(p=0.245; Figure 8).*

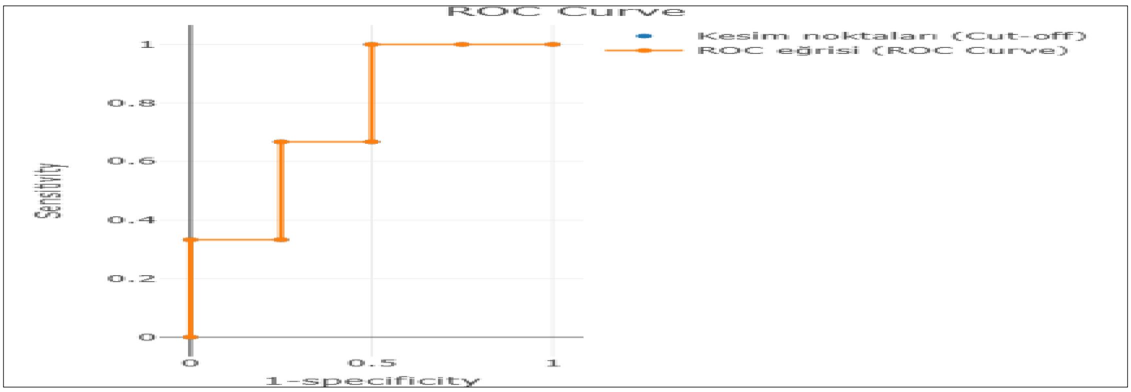

Figure 8. ROC Curve in Determining the Efficiency Status (for o2: Gross Domestic Product Output Variable)

5. DISCUSSION AND CONCLUSION

The study has two main objectives: (i) to assess the efficiency of the ecological footprint of seven G7 countries *(Canada, France, Germany, Italy, Japan, the United Kingdom and the United States)*, (ii) to test the diagnostic performance of input and output variables in determining the efficiency status of the seven G7 countries.

The study has a two-stage analysis design:

- In the first stage, the Input Orientation Slack-Based Data Envelopment Analysis (DEA) model was employed using three input variables (Investment by Asset, Labour Force Participation Rate and Total Energy Consumption) and two output variables (Ecological Footprint (undesirable) and Gross Domestic Product).
- In the second stage, ROC Analysis was conducted to assess the diagnostic performance of the input and output variables in determining the Efficiency Status of G7 countries.

According to the first stage of the analysis design;

- Four G7 countries (Germany, Italy, the United Kingdom and the United States) have a score of 1, and they are relatively efficient. This finding is in line with (Gavurova et al., 2018), in terms of Germany, Italy, and the United Kingdom, in line with (Khezri et al., 2023; Mamghaderi et al., 2023) in terms of the United Kingdom and in line with (Özkan & Özcan, 2018), in terms of Italy, the United Kingdom, and the United States. However, three G7 countries (Canada, France and Japan) are inefficient. This finding is in line with (Hsu et al., 2023; Khezri et al., 2023) in terms of all inefficient DMUs and in line with (Özkan & Özcan, 2018) in terms of France and Japan.
- All four efficient G7 countries rank first, while Japan ranks last among the seven G7 countries. This finding is in line with (Grigoroudis & Petridis, 2019; J. Li et al., 2024).
- Italy are the most appeared DMU in the reference sets with three peer counts. This finding confirms that Italy was marked as efficient during the wholly analysed period finding determined by (Gavurova et al., 2018).
- Besides, although the United States is efficient, they have not appeared in the reference sets. This finding confirms that the United States has the lowest environmental and ecological footprint efficiencies finding determined by (Khezri et al., 2023).
- When improvement options (reducing the inputs or increasing the outputs) for inefficient G7 countries are examined;
  - ✓ DMU that needs the most improvement in terms of i1: Investment by Asset input variable is Japan. The fact that Japan has the highest i1: Investment by Asset value in our dataset is believed to be the cause of this.
  - ✓ DMU that needs the most improvement in terms of i2: Labour Force Participation Rate input variable is Canada. It is thought that this situation is resulting from Canadas has more women working than ever before and high levels of immigration (Bank of Canada, 2026).
  - ✓ DMU that needs the most improvement in terms of i3: Total Energy Consumption input variable is Japan. This is assumed to be caused by Japan having the highest value of i3: total energy consumption (excluding the United States, which is an efficient DMU) in our data.
  - ✓ DMU that needs the most improvement in terms of o1: Ecological Footprint (undesirable) output variable is Canada. This issue is believed to be brought on by Canada's high o1: Ecological Footprint (undesirable) value in our dataset.
  - ✓ DMU that needs the most improvement in terms of o2: Gross Domestic Product output variable is Japan. According to our dataset, Japan's Gross Domestic

Product output variable value is the lowest in the dataset, which is believed to be the reason for this.

According to the second stage of the analysis design;

- It was determined that i1: Investment by Asset input variable could distinguish the Efficiency Status with the cutoff points (21.723).
- i2: Labour Force Participation Rate, i3: Total Energy Consumption input variables, and o1: Ecological Footprint and o2: Gross Domestic Product output variables were not identified as the diagnostic factor in determining Efficiency Status.

It is hoped that the findings of this study will help G7 countries' environmental management institutions and organisations implement more effective ecological footprint policies, at least partially. The most significant of these benefits is believed to be the chance for inefficient G7 countries to improve their ecological footprint and environmental management policies, including the financial and non-financial expenditures in terms of national accounts, by closely examining, contrasting, and modelling the practices of G7 countries in the reference sets identified for them. Furthermore, for the relevant organisations of inefficient G7 countries to reorganise their ecological footprint policies, the cut-off values of Investment by Asset input variables are essential. It is therefore advised that researchers in the areas of ecological footprint and environmental management use ROC analysis and integrated Network Data Envelopment Analysis to evaluate performance on larger samples using various input/output bundles.

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