

Economic and Environmental Efficiency Analysis of Asia-Pacific Region Countries:

Analysis Based on the DEA Model

Arijit Banerjee

Assistant Professor, Shibpur Dinobundhoo Institution

Email: arijitbanerjee1978@gmail.com

Abstract

To achieve sustainable development goals, the world needs strong policies and actions to reduce environmental problems such as global warming and calamities resulting from elevated CO₂ and other harmful emissions, as well as their impacts on economic development. Environmental efficiency is identified in the first phase, whereas economic development efficiency is identified in the latter phase. Environmental and economic development efficiencies were measured using Data Envelopment Analysis (DEA). In economic development efficiency, there are desirable outputs, whereas when measuring environmental efficiency, the output is undesirable. Therefore, we used both radial and non-radial DEA technologies. For radial DEA technology, the BCC and CCR models are used under the assumption of CRS and VRS. For non-radial DEA Technology, the slack-based model is used under the assumption of CRS and VRS. This study compares the economic development and environmental efficiencies of the Asia-Pacific region of the Asia continent. The findings indicate that in the environmental efficiency, the Southeast region, with a scale efficiency score of 0.964, dominates the South region (scale efficiency score 0.833) and the East Region (scale efficiency 0.741), whereas in economic development efficiency, the East region dominates with an efficiency score of 0.52, the other two regions. In terms of environmental efficiency, Indonesia, Malaysia, Nepal, Sri Lanka, and South Korea are the most efficient countries in the Asia-Pacific region. In terms of economic development efficiency, Singapore and Macao are the most efficient countries, with an efficiency score of 1. However, using the super efficiency model, we found that Singapore is the most economically efficient country and South Korea is the most environmentally efficient country in this region. There is no significant association between the ranking according to economic development efficiency and environmental efficiency.

Keywords: Asia-Pacific region, Radial DEA and non-radial DEA, Slack-based model, Environmental index, Economic Development Index.

INTRODUCTION

An evaluation of the environmental energy assessment will be carried out over time (Finnveden et al., 2003), and the researchers' objectives are to lessen the amount of carbon dioxide emissions and the amount of energy that is utilised during production (Min et al., 2022). Based on carbon dioxide emissions in energy policy, preliminary research has provided suggestions for future rules that may be implemented (Morgan & Keith, 2008). This model offers substantial implications for the assessment and decision-making processes for environmental efficacy (Ascough et al., 2008). The persistent release of greenhouse gases is a concerning indicator of rising air temperatures and climate change (Solomon, 2010). According to the most recent report by the Intergovernmental Panel on Climate Change (IPCC, 2014), global CO₂ emissions could not exceed 3000 Gt, and temperatures would rise by 2°C by the end of 2020. End-use technology can reduce carbon emissions by up to 75%. (Schipper, L., 1997). Government laws may promote various paths to recycling and energy cogeneration in sustainable frameworks.(Capodaglio, A. G., 2016) In 2023, the Asia-Pacific area was responsible for almost forty per cent of the world's gross domestic product (GDP), (World Bank, 2024). This region has emerged as one of the most dynamic contributors to global economic expansion. East Asia, South Asia, and Southeast Asia have all experienced fast economic growth during the past three decades as a result of rapid industrialisation, urbanisation, and increased energy consumption (Storper, M. 1997). For example, China's gross domestic product (GDP) reached 25,020.46 billion USD from 2014 to 2023, making it the economic leader in the region. India, with a GDP of 10,461.98 billion USD, and Japan, with a GDP of 5,615.03 billion USD, closely followed China (Our World in Data, n.d.). While this was going on, smaller economies like Singapore, Hong Kong, and Macao displayed extraordinarily high levels of efficiency (Lam, N. M. 2015). These economies also had urbanisation rates of 100 per cent, which highlighted the structural diversity of the region (Henderson, J. V. 2003).

On the other hand, this extraordinarily rapid economic expansion has resulted in a considerable environmental cost (Commoner, B. 2013). China alone was responsible for 10,627 million tons of carbon dioxide emissions during the study period (Wang, H., 2015), while India contributed an additional 2,535 million tons throughout the same period (Garg, P., 2012). The Asia-Pacific region is now responsible for nearly half of the world's CO₂ emissions (Filimonova, 2022). Other growing economies, such as Indonesia and Vietnam, are also experiencing significant increases in emissions (Vo 2019). This is mostly due to their strong reliance on coal-fired electricity and the expansion of industrial bases. On the other hand, countries with a lower population, such as Nepal and Sri Lanka, make a negligible contribution to the overall emissions of the world, but they continue to be susceptible to the environmental deterioration that is brought on by pollution and climate change (Dasvarma, G. 2003).

Problem Statement

The Asia Pacific region comprises both developed countries, such as Singapore, Japan, and Malaysia, and developing countries, such as India, Pakistan, and Sri Lanka. Developed countries have made significant progress in economic growth, whereas developing countries face challenges in balancing economic growth and environmental sustainability. Moreover, a high GDP is not always a sign of high efficiency. Balancing economic growth with environmental sustainability has become a central challenge in development policy in the Asia-Pacific region. This divergence underscores the paradox faced by policymakers: economically efficient countries are not necessarily environmentally efficient and vice versa. Against this backdrop, it is essential to evaluate how efficiently Asia-Pacific countries can convert inputs into desirable outputs, such as GDP and urbanisation, while minimising undesirable environmental outputs, such as CO₂ and NH₄ emissions. Therefore, it is high time to measure the efficiency of the Asia-Pacific region countries regarding economic growth and environmental issues.

Novelty of the Study

Data Envelopment Analysis has been used to measure the efficiencies of countries in the Asia-Pacific region. Economic development efficiency measures favourable output, which means that more output in a given set of inputs increases efficiency, whereas environmental efficiency is measured by undesirable output, which means that more output in a given set of inputs reduces efficiency. Data Envelopment Analysis (DEA), both radial (CCR and BCC) and non-radial (Slack-Based Model), provides a rigorous methodology for assessing this dual performance. Furthermore, the use of the Super Efficiency DEA model allows us to distinguish top performers when multiple countries achieve efficiency scores of unity.

We measure and compare the economic development and environmental efficiencies of 17 Asia-Pacific countries between 2014 and 2023, with an emphasis on identifying the most efficient performers and exploring whether there is any significant association between the two dimensions of efficiency. By integrating both development and environmental perspectives, the paper contributes to the broader discourse on sustainable growth in the Asia-Pacific region and provides empirical evidence to guide policy interventions.

Literature review

Delfin (2025) introduced a weight-restricted DEA under variable returns to scale to evaluate the allocative, technical, and revenue efficiency of 38 APEC ports, providing critical

insights for maritime logistics. Similarly, Wang et al. (2024) employed a DEA with undesirable outputs to assess the efficiency of renewable energy consumption across 21 APEC economies and found that Japan, South Korea, Brunei, and Hong Kong lead in performance. Debbarma, J., Kumar, V., & Ekundayo, D. (2025) measured the carbon emission of manufacturing firms and interpreted it on the basis of sustainability and non-sustainability. Estevão, J., & Lopes, J. D. (2024) showed that disaggregated data improve explanatory power and forecasting in renewable energy consumption, highlighting the growing importance of R&D and innovation in energy transition. Wang et al. (2023) used DEA and SBM for measuring environmental efficiency. Mo et al. (2020) advanced interval DEA models to account for undesirable outputs, while Kitahara and Tsuchiya (2024) reformulated super-efficiency DEA by minimising second-best scores to better rank efficient decision-making units (DMUs). Zhanxg et al. (2025) applied eco-efficiency measures to explore how provincial efficiency in China affects citizen co-production in environmental governance, reporting positive spillover effects.

Hermoso-Orzáez et al. (2020) analysed the environmental efficiency of EU countries using fossil energy and emissions, while Ren et al. (2021) applied a two-stage dynamic DEA model to measure energy, emissions and agricultural disaster efficiency in China. Rebolledo-Leiva et al. (2019) and Rodrigues et al. (2019) offered comparative methods for eco-efficiency in production systems, later influencing applications in Asia. Sun, S., & Liu, Y. (2023). Studies in Anhui Province (2021–2020) revealed eco-efficiency trends in logistics using DEA-BCC and Malmquist indices, with improvements up to 2019, before a decline in 2020. Kourtit, K., Nijkamp, P., & Suzuki, S. (2023) used a line of work assessing “stellar” Asian cities (2022– 2023), using cascade DEA to evaluate capability and performance across 12 metropolitan regions. Wu et al. (2023) highlighted sustainable urbanisation efficiency in Southeast Asia through extended DEA models. Djellouli et al. (2022) revealed that non-renewable energy has a positive effect, while renewable energy shows a negative effect, and the Environmental Kuznets Curve hypothesis does not hold. Zhou et al. (2022) examined carbon efficiency using DEA with common weights, while Du and Wang (2021) applied super-efficiency DEA to evaluate low-carbon cities. Chen and Golley (2021) linked structural change with energy efficiency in East Asia. Lozano and Gutiérrez (2021) employed dynamic DEA to measure sustainability progress.

Shah et al. (2019) investigated green productivity growth in Asia using Malmquist–DEA methods. Chen and Golley (2014) assessed structural change and energy efficiency in East Asia. Xu et al. (2024) used super-efficiency DEA for evaluating low-carbon cities. Huanget al.

(2014) incorporated undesirable outputs in global eco-efficiency measurement. Honma and Hu (2014) analysed Japan's regional energy efficiency. Lin and Du (2015) evaluated energy efficiency across 30 Chinese provinces, while Wang et al. (2017) incorporated urbanisation into eco-efficiency studies. Kumar, S., & Managi, S. (2016) examined environmental DEA models in developing countries.

Research gap

Although current research has extensively utilised DEA to assess either economic or environmental efficiency, there is a paucity of studies that concurrently incorporate both dimensions across Asia-Pacific nations employing radial, non-radial and super-efficiency models. Furthermore, most previous studies have concentrated on either single-country evaluations or regional clusters, neglecting to compare cross-country disparities in scale efficiency, pure technical efficiency, and slack-based judgments of unwanted outcomes. The absence of research that tackles the simultaneous task of fostering economic growth and mitigating environmental deterioration within a cohesive DEA framework presents a significant gap in the literature. The insufficient investigation into the statistical correlation between economic development and environmental efficiency underscores the necessity for more substantial empirical evidence. This study seeks to address these deficiencies by concurrently examining the economic and environmental efficiency of 17 Asia-Pacific nations from 2014 to 2023, thereby providing new perspectives on sustainable policy development.

Objectives

- 1) To measure the efficiency of the Asia-Pacific countries in the Asia continent based on economic development indices.
- 2) To measure the efficiency of the Asia-Pacific region countries in the Asia continent based on environmental indices.
- 3) To obtain the most economically developed efficient country in the Asia-Pacific region countries in the Asia continent.
- 4) To obtain the most environmentally efficient country among the Asia-Pacific countries in the Asia continent.
- 5) Whether there is any significant association between economic development efficiency and environmental efficiency.

Research methodology

Data Source

The research relies on secondary data. To enhance the study's analytical and scientific rigour and to reach definitive results, secondary data is gathered from the World Bank IEA handbook. The period for the study is 10 years, from 2014 to 2023.

Variable Selection

There is no one index to represent economic development or environmental efficiency. However, we still select some inputs and outputs to perform the DEA. Energy production and labour force are used as inputs, and economic output is measured by Real GDP and % of urbanisation. Whereas for measuring the environmental efficiency, we use the same inputs, and we consider the CO₂ emission and NH₄ emission as the outputs.

For Economic development efficiencies

Input	Output
Electricity production in trillion-watt hours	Real GDP in \$ (billion)
Labour force in million	% of urbanisation

For environmental efficiencies

Input	Output
Electricity production in trillion-watt hours	CO ₂ emission in tons (million)
Labour force in million	NH ₄ emission in tons (million)

DMU selection

The Asia–Pacific region is a broad geographic term used in economics, politics, and business to describe the countries and territories located in or near the western Pacific Ocean, covering parts of East Asia, South Asia, and Southeast Asia of the Asia continent. The following countries are selected from each region based on Data availability and GDP of 2024.

South East Asia	South Asia	East Asia
Indonesia	India	China

Thailand	Pakistan	Japan
Philippines	Bangladesh	South Korea
Vietnam	Srilanka	Taiwan

Singapore	Nepal	Hongkong
Malayasia		Macao

Radial DEA (Data Envelopment Analysis) Approach

Data Envelopment Analysis is a linear programming methodology (Charnes, A., Cooper, W. W., & Rhodes, E., 1978). The performance of DMUs is evaluated in Data Envelopment Analysis (DEA) defined as the ratio of total outputs to total inputs (Charnes, A., & Cooper, W. W., 1963).

$$\text{Efficiency} = \frac{\text{Output}}{\text{Input}}$$

Output-oriented Model

Efficiency can be measured in two ways: one is input minimisation, and the other is output maximisation (Cooper WW, Huang Z, Li SX, 1996). The first one is called the input-oriented DEA model, and the other one is called the output-oriented DEA model. In the output-oriented model, the main focus is to maximise the increase in the output without changing the input quantity (Charnes, A., & Cooper, W. W., 1969). In this paper, we used the output orientation method because producing more output, i.e. GDP and % of urbanisation, with a given input, i.e electricity production and labour force, is more acceptable.

In an output-oriented method, the main objective is output maximisation (Schüler, W. 1977). In an output-oriented model, the input level (x_1 , x_2 , or x_3) remains constant while output amounts are correspondingly increased until the frontier is attained. For every DMU A, the output-oriented projection onto the frontier is represented by the point $P^* A$, where output y_1 is generated from input x^*1 . Likewise, for DMU B, the output-oriented projection is represented by point $P^* B$, indicating the output level y_2 generated from input x^*2 . The duo of output-focused technical efficiency metrics for the two companies is as follows:

$$TE \text{ of DMU A} = \frac{y^* A}{yA} \leq 1$$

Similarly, the technical efficiency of Firm B is as follows:

$$TE \text{ of DMU B} = \frac{y^* B}{yB} \leq 1$$

1.1. Technical efficiency – CCR model (Charnes, Cooper and Rhodes, 1978)

Maximise θ

$$\sum_{j=1}^n \lambda_j X_j \leq X_o \quad \dots (1) \text{ (for all inputs)}$$

$$\sum_{j=1}^n \lambda_j Y_j \geq \theta Y_o \dots (2) \text{ (for all outputs)}$$

$$\lambda_j \geq 0 \dots (3) \text{ (for all } j=1,2, \dots n)$$

n= No of DMUs. Here n=17

X_o = Input vectors of DMU₀.

Y_o = Output vectors of DMU₀.

X_j = Input vector of jth DMU

Y_j = Output vector of jth DMU

θ = The efficiency score for DMU₀, representing the scaling factor by which the outputs can be increased while keeping the same level of inputs. The goal is to maximise this score.

λ_j = A vector of weights assigned to the jth DMU

$\theta=1$: This means that DMU₀ is efficient under the constant returns to scale assumption, and its outputs cannot be increased without increasing inputs.

$\theta>1$: This indicates that DMU₀ is inefficient, and it has the potential to increase its outputs by a factor of $\theta-1$ without requiring additional inputs.

Pure Technical Efficiency – BCC model (Banker, Charnes and Cooper, 1984)

A variable return to scale means outputs are changed in a different proportion as compared to inputs. It may be increased or decreased. Unlike the CRS model, VRS allows for non-proportional scaling of inputs and outputs. This means that a DMU may not necessarily experience a proportional increase in outputs when its inputs are scaled up or down.

For a given DMU₀ the output-oriented CRS model can be formulated as a linear programming problem

Maximise θ

$$\sum_{j=1}^n \lambda_j X_j \leq X_o \quad \dots (1) \text{ (for all inputs)}$$

$$\sum_{j=1}^n \lambda_j Y_j \geq \theta Y_o \dots (2) \text{ (for all outputs)}$$

$$\sum_{j=1}^n \lambda_j = 1 \dots (3) \text{ (VRS condition)}$$

$\lambda_j \geq 0 \dots (4)$ (for all $j=1,2, \dots n$)

n = No of DMUs. Here $n=21$

X_0 = Input of DMU₀.

Y_0 = Output of DMU₀.

X_j = Inputs of j th DMU

Y_j = Outputs of j th DMU

θ = efficiency score of DMU

λ_j = A vector of weights assigned for j th DMU

The goal is to maximise this score.

λ_j = A vector of weights assigned to the j th DMU.

Scale efficiency (SE = TE / PTE)

Technical efficiency is under the assumption that CRS measures operational efficiency as well as scale efficiency (Banker, R. D., & Gifford, J. L., 1988).

Whereas Pure technical efficiency is assumed to be VRS, that assumption presents efficiency without considering the scale of operation (Banker, R. D., & Chang, H., 1995). It results in inefficiency, resulting from underperformance.

$$\text{Scale Efficiency} = \frac{TE}{PTE}$$

Non-Radial DEA

In DEA, a non-radial method is a type of efficiency measurement approach where inputs and/or outputs are allowed to change non-proportionally when projecting a Decision-Making Unit (DMU) onto the efficiency frontier. In the case of environmental efficiency, outputs are undesirable (Zhou, P., Poh, K. L., & Ang, B. W., 2007). We utilised the Slack-based model for efficiency measurement.

Slack-Based Model (Tone, 2001) for undesirable output

The Slack-Based Measure of efficiency (Tone, 2001) is a non-radial DEA model that directly incorporates slacks (input excess and output shortfall) into the efficiency score.

Unlike radial DEA, it doesn't assume that all inputs or outputs change proportionally. Instead, it measures inefficiency as the average proportional slack across all inputs and outputs (Cooper, W. W., & Tone, K., 1997).

Minimise inefficiency

$$\min \rho = \frac{1 - 1/m \sum_{i=1}^m s^- / x_{io}}{1 + 1/s \sum_{r=1}^s s^+ / y_{ro}}$$

Subject to

$$\sum_{j=1}^n \lambda_j x_{ij} + s_i^- = x_{io} \quad i = 1, \dots, m$$

$$\sum_{j=1}^n \lambda_j y_{rj} - s_r^+ = x_{ro} \quad r = 1, \dots, m$$

n = number of DMUs

m, s = number of inputs and outputs

x_{ij} = amount of input i used by DMU j

y_{rj} = amount of output r produced by DMU j

x_{io}, y_{ro} = observed inputs/outputs for the DMU under evaluation (o)

s_i^- = input slack (extra input to remove)

s_r^+ = output slack (shortfall to improve)

λ_j = intensity variable (convex combination of reference DMUs)

The numerator measures the average proportional reduction in inputs possible.

If all $s_i^- = 0$, numerator = 1 (fully efficient).

The denominator measures the average proportional increase in outputs possible.

If all $s_r^+ = 0$, denominator = 1 (no output shortfall).

The ratio ρ is always in $(0,1)$ with **1** meaning fully efficient.

Spearman's Rank Correlation

Spearman's rank correlation evaluates how well the relationship between two variables. The coefficient, denoted as ρ , ranges from -1 (perfect negative correlation) to +1 (perfect positive correlation), with 0 indicating no monotonic relationship.

$$\text{Spearman's rank Correlation} = \rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

Where

$d_i = R(X_i) - R(Y_i)$: The difference between the ranks of corresponding values of X_i and Y_i .

$R(X_i)$ The rank of X_i

$R(Y_i)$: The rank of Y_i

n : The number of observations.

Kendall's Tau Correlation

To check the relation more robustly, we use Kendall's Tau Correlation. Kendall's Tau correlation is a non-parametric statistic used to measure the strength and direction of association between two variables. The mathematical expression for Kendall's Tau (τ) correlation coefficient is:

$$\frac{Nc - Nd}{\sqrt{(Nc + Nd + Ty)(Nc + Nd + Tx)}}$$

Where:

- Nc: The number of concordant pairs.
- Nd: The number of discordant pairs.
- Ty: Number of ties observation of the dependent variable.
- Tx: Number of ties observation of the independent variable.

Super Efficiency DEA model (Andersen, P., & Petersen, N. C., 1993) Nonetheless, a significant constraint of conventional DEA is that several DMUs may get an efficiency score of 1, complicating their ranking (Adler, N, et al, 2002) In the above Data Envelopment Analysis under the output-oriented model, more than 1 DMU scored an efficiency score of 1. So, it is difficult to state which DMU is most efficient in economic development and environmental efficiency.

Andersen, P., & Petersen, N. C. (1993) introduced the Super-Efficiency DEA Model to resolve this issue, permitting efficiency ratings beyond 1 and facilitating the ranking of efficient DMUs.

The Super-Efficiency DEA Model is a significant enhancement of DEA that facilitates the ranking of efficient Decision-Making Units (DMUs). Eliminating the target DMU from the reference set facilitates efficiency ratings exceeding 1, hence identifying the top performers among efficient DMUs.

n = Number of **DMUs** (decision-making units)

m = Number of **inputs**

s = Number of **outputs**

x_{ij} = Input i of DMU j (where $i=1, 2, \dots, m$)

y_{rj} = Output r of DMU j (where $r=1, 2, \dots, s$)

λ_j = Weight (intensity variable) assigned to DMU j

o= The target DMU being evaluated

θ = Efficiency score (input-oriented)

ϕ = Efficiency score (output-oriented)

Output-Oriented Super-Efficiency Model

Objective: Maximise ϕ

Subject to: $\sum_{j \neq 0} \lambda_j x_{ij} \leq x_{io}, \forall i=1,2, \dots, m$

$\sum_{j \neq 0} \lambda_j y_{rj} \geq \phi y_{ro}, \forall r=1,2, \dots, s$

$\lambda_j \geq 0, \forall j \neq 0$

The following are the Key Differences from the Standard DEA

- Exclusion of DMU o: Unlike standard DEA, DMU o is removed from the reference set.
- Efficiency Score θ or ϕ Can Be Greater Than 1: If θ or $\phi > 1$, the DMU is super-efficient.
- Interpretation:
 - o θ or $\phi < 1 \rightarrow$ Inefficient DMU (can improve input efficiency)
 - o θ or $\phi = 1 \rightarrow$ Efficient DMU
 - o θ or $\phi > 1 \rightarrow$ Super-efficient DMU, ranked higher than standard-efficient DMUs.

DATA ANALYSIS

Economic development efficiency

Table 1. 10-year average data in million for input and output variables of selected Asia Pacific countries from the year 2014 to 2023

DMU	Electricity production in trillion-watt hour EP({I}	Labour Force (million) LF{I}	Gross Domestic Product in \$ million) GDP{O}	% of Urbanisation URBAN{O}
Indonesia	286.88	133.84	3305.96	55.63
Thailand	179.61	40.18	1431.38	50.30
Philippines	98.63	44.93	956.69	47.09
Vietnam	217.03	55.50	1073.59	36.28
Malayasia	168.46	16.35	987.49	76.25
Singapore	53.37	3.42	668.68	100.00
India	1572.37	531.56	10461.98	34.30
Bangladesh	81.17	68.25	1087.83	37.01
Pakistan	139.69	73.79	1177.70	36.85
Srilanka	9.31	8.52	299.56	18.60
Nepal	5.95	7.86	122.45	19.98
China	7363.47	776.41	25020.46	59.60
Japan	1046.33	67.78	5615.03	91.66
South Korea	583.27	17.13	2375.42	81.50
Taiwan	274.35	23.33	655.59	78.69
Hongkong	37.05	3.90	475.17	100.00
Macao	0.79	0.40	73.12	100.00

In the above table, we find the data for 16 Asian economies. China leads in electricity production (7,363.47 trillion watt hours) and GDP (25,020.46 million \$), while India has the

second-largest electricity output and labour force. Smaller economies like Macao and Nepal show minimal electricity production and GDP. Urbanisation varies widely, from 18.60% in Sri Lanka to 100% in Singapore, Hong Kong, and Macao.

Table 2. TE (Technical efficiency), PTE (Pure Technical efficiency), and Scale efficiency (SE) score and rank based on the CRS and VRS assumption with the output orientation model.

	DMU	CRS score (TE)	Rank	VRS score (PTE)	Rank	Scale Efficiency	Rank
South East Asia	Indonesia	0.133442	13	1	5.5	0.133442	15
	Thailand	0.190534	9	0.860694	11	0.221372	9
	Philippines	0.115017	14	0.778651	13	0.147713	13
	Vietnam	0.103709	16	0.532977	17	0.194585	10
	Malaysia	0.315321	7	0.775842	14	0.406424	6
	Singapore	1	1.5	1	5.5	1	1.5
South Asia	India	0.105955	15	1	5.5	0.105955	17
	Bangladesh	0.144403	12	1	5.5	0.144403	14
	Pakistan	0.090836	17	0.694267	15	0.130838	16
	Sri Lanka	0.346638	6	1	5.5	0.346638	8
	Nepal	0.221852	8	0.582591	16	0.380803	7
East Asia	China	0.168793	10	1	5.5	0.168793	12
	Japan	0.42344	5	1	5.5	0.42344	5
	South Korea	0.708219	3	1	5.5	0.708219	3
	Taiwan	0.145831	11	0.788984	12	0.184834	11
	Hongkong	0.637349	4	1	5.5	0.637349	4
	Macao	1	1.5	1	5.5	1	1.5

The DEA results show that Singapore and Macao achieved full efficiency (CRS, VRS, and scale efficiency = 1), ranking highest. When the efficiency score is equal for more than 1 DMUs, then we use statistical ranking, i.e. Macao and Singapore both have an efficiency score of 1, so both of their rank will be $(1+2)/2=1.5$. South Korea (0.708), Hong Kong (0.637), and Japan (0.423) also performed well. Several countries, including Indonesia, India, Bangladesh, China, and Sri Lanka, achieved full VRS efficiency but low scale efficiency, indicating scale-related inefficiencies. Whereas Vietnam and Pakistan are at the bottom in CRS efficiency. Pakistan and Nepal are at the bottom in VRS efficiency. Pakistan is at the bottom in scale efficiency. China, Japan, Hong Kong, and Malaysia showed relatively high scale efficiency among the Asia-Pacific countries.

Table 3. Average TE, PTE, and SE economic development scores and rank of South East Asia, South Asia and East Asia region

Asia Pacific Region	Avg Score_CRS (TE)	Rank	Avg Score_VRS (PTE)	Rank	Avg Scale Efficiency	Rank
South East Asia	0.3096	2	0.8246	3	0.3505	2
South Asia	0.1819	3	0.8553	2	0.2217	3
East Asia	0.5139	1	0.9648	1	0.5204	1

The results show that East Asia outperforms other subregions in economic development efficiency measures, with the highest average Technical Efficiency (0.5139), Pure Technical Efficiency (0.9648), and Scale Efficiency (0.5204), ranking first in each category. South East Asia ranks second in technical efficiency with a score of 0.3096 and Scale Efficiency (0.3505), but falls to third in Pure technical efficiency (0.8246). South Asia consistently ranks third in TE (0.1819) and Scale Efficiency (0.2217), but performs relatively better in PTE (0.8553), securing the second rank. This indicates that East Asia enjoys the economic development efficiency advantage probably comes from a high rate of urbanisation, i.e. Macao and Hong Kong have 100% urbanisation and high GDP, as China has the highest GDP of the countries in this region.

Environmental efficiency

Table 4. 10-year average data in million for input and output variables of selected Asia Pacific countries from the year 2014 to 2023

DMU	Electricity production in trillion-watt hour EP{I}	Labour Force (million) LF{I}	CO2 emission in million Tons{O}	NH4 emission in million Tons{O}
Indonesia	286.88	133.84	607.01	389.98
Thailand	179.61	40.18	276.32	110.68
Philippines	98.63	44.93	132.53	91.85
Vietnam	217.03	55.50	274.51	108.32
Malayasia	168.46	16.35	261.58	59.27
Singapore	53.37	3.42	48.94	5.92
India	1572.37	531.56	2535.90	893.22
Bangladesh	81.17	68.25	92.46	108.73
Pakistan	139.69	73.79	202.48	218.10
Srilanka	9.31	8.52	20.82	12.47
Napal	5.95	7.86	12.79	29.15
China	7363.47	776.41	10627.64	1724.10

Japan	1046.33	67.78	1124.95	31.96
South Korea	583.27	17.13	626.55	41.38
Taiwan	274.35	23.33	276.81	18.04

Hongkong	37.05	3.90	39.08	5.74
Macao	0.79	0.40	1.34	0.12

In the above table, we find the data for 16 Asian economies. China leads in both CO₂ emissions, i.e. 10627 million tons, and NH₄ emissions (1724 million tons), while India has the second-largest CO₂ emissions and NH₄ emissions. Smaller economies like Macao and Nepal show minimal CO₂ and NH₄ emissions.

In the above table, outputs are undesirable, so we used slack slack-based DEA model for data envelopment analysis.

Table 5. TE (Technical efficiency), PTE (Pure Technical efficiency), and Scale efficiency (SE) score and rank based on the CRS and VRS assumption with the output orientation model under the Slack-Based Model

DMU	CRS score (TE)	Rank	VRS score (PTE)	Rank	Scale Effect	Rank
Indonesia	1	3	1	5	1	3
Thailand	0.838635	6	0.881216	10	0.951679	8
Philippines	0.646288	9	0.665906	12	0.97054	6
Vietnam	0.629745	10	0.672805	11	0.935999	9
Malayasia	1	3	1	5	1	3
Singapore	0.592988	12	0.638204	14	0.929151	10
India	0.618724	11	1	5	0.618724	16
Bangladesh	0.494565	14	0.663176	13	0.745752	13
Pakistan	0.80129	7	1	5	0.80129	12
Srilanka	1	3	1	5	1	3
Nepal	1	3	1	5	1	3
China	0.736727	8	1	5	0.736727	14
Japan	0.232178	16	0.327256	17	0.709469	15
South Korea	1	3	1	5	1	3
Taiwan	0.33077	15	0.367629	16	0.899739	11
Hongkong	0.506449	13	0.530973	15	0.953813	7
Macao	0.150325	17	1	5	0.150325	17

Indonesia, Malaysia, Sri Lanka, Nepal, and South Korea achieve perfect scores in CRS

Technical Efficiency, VRS Pure Technical Efficiency, and Scale Efficiency, ranking joint 3rd in CRS and scale rankings, and joint 5th in VRS rankings. India, China, and Macao achieve VRS = 1 but lower CRS scores. India's scale efficiency is very low (0.6187, rank 16). Macao has the lowest scale efficiency (0.1503, rank 17). The Philippines, Vietnam, Singapore, Hong Kong, and Bangladesh show mid-range CRS efficiency (0.49–0.65) and lower VRS scores

(0.53 to 0.67), indicating room for improvement in scale efficiency. Japan (CRS = 0.2322, VRS = 0.3273, Scale = 0.7095) and Taiwan (CRS = 0.3308, VRS = 0.3676, Scale = 0.8997) have low technical efficiency,

Table 6. Average TE, PTE, and SE environmental efficiency scores and rank of South East Asia, South Asia and East Asia region

Asia Pacific Region	Avg Score_CRS (TE)	Rank	Avg Score_VRS (PTE)	Rank	Avg Scale Efficiency	Rank
South East Asia	0.7846	1	0.8096	2	0.9645	1
South Asia	0.7829	2	0.9326	1	0.8331	2
East Asia	0.4927	3	0.7043	3	0.7416	3

The results show that South East Asia outperforms other subregions in economic development efficiency measures, with the highest average Technical Efficiency (0.7846), Pure Technical, and Scale Efficiency (0.9645), ranking first in each category. South Asia ranks second in technical efficiency with a score of 0.7829 and Scale Efficiency (0.8331). East Asia consistently ranks third in TE (0.4927), PTE (0.7043), and Scale Efficiency (0.7416). This indicates that South East Asia enjoys the environmental efficiency advantage, probably coming from low CO₂ and NH₄ emissions.

Super Efficiency Score in economic development efficiency

From the above, it has been observed that in economic development efficiency, some countries scored 1, i.e. they are fully efficient. So among the above countries, we cannot identify the most efficient country. To break up the ties between the DMUs, we use the Super Efficiency Model of Andersen and Petersen (1993).

Table 7. Super Efficiency Score based on CRS, VRS, and SE, under the output-orientation model

	DMU	CRS score (TE)	Rank	VRS score (PTE)	Rank	Scale Efficiency	Rank
South East Asia	Indonesia	0.133442	13	1.0054	10	0.13272528	15
	Thailand	0.190534	9	0.860694	11	0.22137252	9
	Philippines	0.115017	14	0.778651	13	0.14771316	13
	Vietnam	0.103709	16	0.532977	17	0.19458438	10
	Malayasia	0.315321	7	0.775842	14	0.40642425	6
	Singapore	1.0583	2	big	1	infinite	1
South Asia	India	0.105955	15	1.6656	3	0.06361371	17

	Bangladesh	0.144403	12	1.0253	7	0.14083975	14
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	Pakistan	0.090836	17	0.694267	15	0.13083727	16
	Srilanka	0.346638	6	1.0111	9	0.34283256	8
	Nepal	0.221852	8	0.582591	16	0.38080231	7
East Asia	China	0.168793	10	1.10938	4	0.15215075	12
	Japan	0.42344	5	1.0318	6	0.41038961	5
	South Korea	0.708219	3	1.0495	5	0.67481563	3
	Taiwan	0.145831	11	0.788984	12	0.18483391	11
	Hongkong	0.637349	4	1.0161	8	0.62725027	4
	Macao	4.3459	1	4.7021	2	0.92424661	2

In the above table, it has been found that Singapore is the most economic development efficient country in the Asia Pacific region. Macao is ranked 2nd as its scale efficiency score is 0.92. In this way, using the super efficiency, we break the tie position among the most efficient countries. Except for breaking the tie, there is no change in ranking for the other countries.

Super Efficiency Score in environmental efficiency

Table 8. Super Efficiency Score based on Slack-Based CRS, VRS, and SE, under the output-orientation model

	DMU	CRS score (TE)	Rank	VRS score (PTE)	Rank	Scale Effect	Rank
South East Asia	Indonesia	1.1685	3	1.1984	5	0.9750501	4
	Thailand	0.838635	6	0.881216	10	0.9516793	8
	Philippines	0.646288	9	0.665906	12	0.9705394	6
	Vietnam	0.629745	10	0.672805	11	0.9359993	9
	Malayasia	1.2528	3	1.2614	5	0.9931822	3
	Singapore	0.592988	12	0.638204	14	0.9291512	10
South Asia	India	0.618724	11	1.8801	5	0.329091	16
	Bangladesh	0.494565	14	0.663176	13	0.7457523	13
	Pakistan	0.80129	7	1.0079	5	0.7950094	12
	Srilanka	1.0476	3	1.0497	5	0.9979994	2
	Nepal	3.14	3	3.2337	5	0.9710239	5
	China	0.736727	8	1.0376	5	0.7100299	14
	Japan	0.232178	16	0.327256	17	0.709469	15

East Asia	South Korea	2.2192	3	2.2209	5	0.9992345	1
	Taiwan	0.33077	15	0.367629	16	0.8997386	11
	Hongkong	0.506449	13	0.530973	15	0.9538131	7
	Macao	0.150325	17	1.7385	5	0.0864682	17

In the super efficiency model, we break the tie between Indonesia, Malaysia, Sri Lanka, Nepal, and South Korea. We found that South Korea is the most environmentally efficient country among the Asia Pacific countries, with a scale efficiency of almost 1, followed by Sri Lanka (scale efficiency score of 0.997) and Malaysia (0.9921).

Significance of the Association between the ranking

Table 9. Correlation between economic development efficiency rank and environmental efficiency Rank

		Environmental efficiency rank
economic development efficiency rank	ρ	0.189
	df	15
	p-value	0.467
	Kendall's Tau B	0.176
	p-value	0.349
	N	17

Ho: There is no significant association between economic development efficiency ranking and environmental efficiency ranking

The correlation study between the development efficiency ranking and the environmental efficiency ranking using Spearman's rho is shown in the table. Though there is a positive correlation between the 2 rankings, the calculated value < tabulated value in Spearman's rank correlation methods, so we accept Ho, that there is no significant association between economic development efficiency ranking and environmental efficiency ranking of the Asia Pacific countries in the Asia continent. To test the robustness of the above result, we do the Kendall's tau_b test, and the Kendall's tau_b test also gives the same result as Spearman's rank correlation test.

FINDINGS

- 1) The East Asia region is the most efficient in economic development efficiency indices. Singapore and Macao are the most efficient countries among the Asia-Pacific countries in the Asia continent based on economic development indices.
- 2) The Southeast Asia region is the most efficient in environmental efficiency indices. Indonesia, Malaysia, Sri Lanka, Nepal and South Korea are the most efficient countries among the Asia-Pacific countries in the Asia continent based on environmental indices.

- 3) Singapore is the most efficient in economic development indices among the Asia-Pacific countries in the Asia continent.
- 4) South Korea is the most efficient in environmental indices among the Asia-Pacific countries in the Asia continent.
- 5) There is no significant association between economic development efficiency and environmental efficiency.

CONCLUSION

This study set out to measure and compare the economic development efficiency and environmental efficiency of Asia-Pacific countries using both radial and non-radial Data Envelopment Analysis (DEA) models, covering the period from 2014 to 2023. From a methodological perspective, this study demonstrates the strength of **non-radial DEA (slack-based model)** in assessing cases with undesirable outputs, as it allows for a more realistic evaluation of environmental performance than radial models, which assume proportional changes in all inputs and outputs. The analysis was based on electricity production and labour force as inputs, and GDP, urbanisation, and emission indicators (CO₂ and NH₄) as outputs. By applying the CCR, BCC, Slack-Based Measure (SBM), and super-efficiency DEA models, this study provides a comprehensive assessment of efficiency across 17 countries in South Asia, Southeast Asia, and East Asia.

The results indicate that **economic development efficiency** is led by the East Asian region, with the highest overall technical (0.5139), pure technical (0.9648), and scale efficiency scores (0.5204). Within this group, **Singapore and Macao** achieved full efficiency, with an efficiency score of 1. Based on the super-efficiency model, Singapore was identified as the most efficient country.

This reflects the advantage of advanced economies in East Asia, where high levels of urbanisation, innovation, and economic output contribute to superior development efficiency. On the other hand, based on the Slack-based DEA model, the Southeast Asian region dominated the others in **environmental efficiency**, achieving the highest average efficiency scores across the CRS (0.7846), scale measures (0.9645), and 2nd highest in VRS (0.8096). At the country level, **Indonesia, Malaysia, Sri Lanka, Nepal, and South Korea** initially appeared equally efficient, but the super-efficiency model clarified that **South Korea is the most environmentally efficient**, followed closely by Sri Lanka and Malaysia. This outcome highlights how smaller and mid-sized economies with stricter environmental regulations, and lower emissions intensity can outperform larger economies in sustainability metrics.

Importantly, the correlation analysis using Spearman's rho and Kendall's tau confirmed that there is **no significant association between economic development efficiency and environmental efficiency**. This suggests that progress in economic development does not

necessarily align with progress in environmental performance, highlighting the challenges of achieving sustainable development goals. For example, countries such as China and India, while strong in economic output, perform poorly in environmental efficiency due to their high levels of emissions. Conversely, countries such as Nepal and Sri Lanka, despite relatively lower GDP levels, achieve high environmental efficiency.

RECOMMENDATION

Overall, the findings emphasise the **dual challenge facing Asia-Pacific policymakers**: while economic efficiency can be improved through growth-oriented policies, such progress may not translate into environmental sustainability and resilience. Achieving this balance requires targeted interventions, such as investments in clean energy, stricter emission controls, and sustainable urbanisation policies. This research underscores that sustainable development in the Asia-Pacific region cannot be achieved by focusing solely on economic growth; rather, it requires coordinated strategies that integrate economic and environmental priorities.

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