

Article

A Data-Driven Informatics Framework for Evaluating Thai Provinces Using an Additive Weighting-Based Variant Assessment Algorithm and Two-Stage DEA

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Abstract

In order to evaluate regional sustainability, a comprehensive framework is needed that can integrate a number of economic and environmental variables into a transparent and policy-relevant evaluation approach. The present study presents a data-driven informatics framework for the evaluation of Thai provinces that utilizes the additive weighting-based variant assessment algorithm (AWVAA) with Charnes–Cooper–Rhode (CCR)-based two-stage data envelopment analysis (DEA). The system allows three interrelated activities: provincial screening, representative decision-making unit selection, and comparative efficiency benchmarking of economic and environmental performance. AWVAA employs global and local simple additive weighting algorithms in screening 77 provinces to find representative units while keeping regional balance and data completeness. In the second phase, the selected provinces are evaluated by a two-stage DEA structure based on CCR to measure their relative efficiency for transforming development-related inputs into intermediate operational factors and ultimate economic and environmental outputs. The analysis starts with investment, tourist arrivals, and newborns as initial inputs, moves through energy use, electricity consumption, number of factories, and number of vehicles as intermediate variables, and ends with gross provincial product and air quality indicators, including ozone, PM10, and PM2.5 as final outputs. The proposed framework selects 16 typical provinces and shows significant variations in overall CCR efficiency and super-efficiency performance over the selected set. The results suggest that provinces with high screening-stage prominence may not necessarily become the strongest DEA-based standards and emphasize the complimentary roles of representative unit selection and formal efficiency assessment. The study combines multi-criteria screening with benchmarking based on DEA to give a transparent and replicable method for regional sustainability monitoring, comparative assessment, and evidence-based policy planning. The results provide an informatics-oriented paradigm for complicated regional evaluation and practical insights for enhancing sustainable provincial development in Thailand.

Keywords: informatics; regional sustainability; additive weighting-based variant assessment algorithm (AWVAA); two-stage data envelopment analysis (TSDEA); decision support; Thai provinces



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1. Introduction

Sustainable regional development is an increasingly important policy objective in many quickly developing countries, as economic expansion typically increases pressure on natural systems. This dilemma is most evident at the provincial level in Thailand where disparities in industrial activity, tourism intensity, energy use, and urban growth have created uneven patterns of economic opportunity and environmental stress. Hence, the performance of a province cannot be judged only on the basis of economic metrics. Furthermore, a fairer assessment needs to take into account environmental consequences, in particular air quality, which directly impacts public health, quality of life, and long-term development potential.

In this environment, regional evaluation is as much a policy challenge as a data integration problem. Provincial performance must be assessed along a number of axes, such as economic input, operational activity, and environmental output, all of which are expressed in different units and often reflect competing agendas. This makes the evaluation process a suitable candidate for an informatics-oriented approach where heterogeneous data may be categorized, screened, converted, and analyzed to enable transparent and evidence-based decision-making. A look through the informatics lens enables policymakers to see provinces not as a single-indicator ranking exercise but as complex decision-making units whose performance is the outcome of interconnected economic and environmental processes.

A recurring drawback of the available literature is that economic and environmental performance are generally analyzed in isolation. Many studies only focus on economic productivity, while others focus on environmental quality or pollution control in isolation. Although such approaches provide useful partial insights, they do not fully capture the trade-offs involved in sustainable regional development. A province may perform strongly in economic terms while generating substantial environmental burdens, whereas another may maintain better environmental quality but exhibit weaker economic performance. For this reason, an integrated framework is needed to evaluate how provinces balance both dimensions simultaneously.

Data envelopment analysis (DEA) has been widely applied to evaluate the relative efficiency of decision-making units with multiple inputs and outputs. Two-stage DEA is particularly relevant when performance is generated through a sequential structure, where initial inputs first influence intermediate operational factors and these, in turn, shape final outcomes. In regional sustainability studies, this structure is useful because economic and demographic inputs can be linked to intermediate variables such as energy use, factory activity, electricity consumption, and vehicle density before being associated with broader economic and environmental outputs such as gross provincial product and air quality. Even so, the usefulness of DEA-based regional analysis depends heavily on the selection of representative units for evaluation. If the screening stage is weak or unbalanced, the subsequent efficiency analysis may not provide meaningful policy guidance.

To address this issue, this study proposes a data-driven informatics framework that integrates an additive weighting-based variant assessment algorithm (AWVAA) with Charnes–Cooper–Rhode (CCR)-based two-stage data envelopment analysis. The role of AWVAA is to support the structured screening and selection of representative provinces from a larger national dataset. AWVAA does not depend on a single ranking process. Instead, it employs global and local simple additive weighting processes to guarantee regional representation and to determine which provinces have enough complete and relevant data for further assessment. This stage is followed by a DEA evaluation based on CCR that evaluates the relative efficiency of the selected provinces and provides a comparative benchmarking of economic and environmental performance. Thus, the framework integrates multi-criteria screening with formal efficiency evaluation in a single decision-support structure.

It should be mentioned that AWVAA is not put forward as a brand new MCDM theory but as an integrated screening algorithm built up from well-known multi-criteria decision-making ideas, especially simple additive weighting (SAW), normalization-based variant evaluation, and composite-score combination. The methodological contribution of this study is to assemble these existing MCDM components to develop a transparent and reproducible mechanism for representative province selection prior to the CCR-based two-stage DEA assessment.

The suggested framework makes three contributions to the literature. First, it presents an integrated approach that connects provincial screening and performance evaluation, rather than considering them as distinct analytical jobs. Second, it provides a systematic approach for comparative benchmarking of economic production and environmental sustainability by means of overall CCR efficiency and super efficiency evaluation. Third, it places the analysis in a broader informatics context by focusing on transparency, reproducibility, and policy usability in the handling of regional data. Therefore, the study aims not only to identify representative provinces but also to build a viable analytical framework that can support regional benchmarking, sustainability monitoring, and evidence-based policymaking.

Thailand is an appropriate empirical setting for this analysis because its regions demonstrate considerable variability in economic structure, intensity of tourism, concentration of industry, and environmental circumstances. These contrasts make Thailand an excellent case study for exploring how data-driven regional evaluation might uncover both well-performing and under-performing provinces. In this study, representative provinces are selected during the screening step and their relative efficiency is compared at the evaluation stage, thereby producing helpful findings for policymakers concerned about sustainable provincial development. Accordingly, the objectives of this study are:

- (1) To develop an informatics-oriented framework for screening and evaluating Thai provinces using AWVAA and CCR-based DEA;
- (2) To identify representative decision-making units from the national provincial dataset through a structured multi-criteria screening procedure;
- (3) To assess and benchmark the relative performance of the selected provinces using overall CCR efficiency and super-efficiency evaluation.

The rest of this paper is structured as follows. Section 2 presents a literature analysis on regional sustainability assessment, multi-criteria decision making, and performance evaluation based on DEA. The associated methodologies of the study are described in Section 3. In Section 4, we propose a data-driven informatics approach that integrates AWVAA-based representative provincial screening and CCR-based DEA evaluation. Section 5 includes the empirical results and discussion, focusing on comparative benchmarking and the relationship between prominence at the screening stage and performance at the efficiency stage. Section 6 closes the study and gives directions for future research.

2. Literature Review

Regional sustainability is increasingly a multi-disciplinary topic. It demands the integration of economic, environmental, and decision-analytic viewpoints. This topic has been quite relevant in recent years for informatics as well, especially in the setting of transforming various datasets into structured evidence for planning, benchmarking, and policy assistance. The main challenge of regional and environmental assessment is not only to measure performance but also to organize disparate indicators into a useful analytical system to identify significant trends across decision-making units (DMUs). We need systems that can process many inputs, intermediary elements, and final conclusions at the same time to analyze province-level data.

A substantial body of research has examined the relationship between economic development and environmental quality, especially in relation to air pollution and sustainability outcomes. Wang et al. [1] evaluated urban environmental performance in China and highlighted the need to balance economic production with environmental protection. Krmac and Djordjević [2] compared one-stage and two-stage DEA models in assessing port environmental efficiency, showing that multi-stage structures can yield more nuanced insights than conventional single-stage evaluations. Othman et al. [3] examined air-pollution-related environmental performance in Malaysia using DEA, slack-based measures, the Malmquist productivity index, and principal component analysis, demonstrating the growing interest in combining operational efficiency analysis with environmental indicators. Similarly, Yang et al. [4] studied government investment efficiency in air pollution control, while Zheng et al. [5] assessed green total factor energy efficiency and pollution reduction in China. Collectively, these studies confirm that environmental performance is deeply intertwined with economic activity and that sustainability assessment requires models capable of reflecting this interaction.

Alongside this environmental literature, multi-criteria decision-making (MCDM) approaches have been widely used to rank alternatives when multiple and often conflicting indicators must be considered simultaneously. Among these methods, simple additive weighting (SAW) remains one of the most widely applied because of its transparency, interpretability, and ease of implementation. Ghaemi-Zadeh and Eghbali-Zarch [6] incorporated SAW alongside D-CRITIC, fuzzy MULTI-MOORA, TOPSIS, VIKOR, and other methods in business strategy evaluation. Wati et al. [7] compared SAW with TOPSIS and MOORA in socio-economic welfare evaluation, while Tirkolaee et al. [8] used SAW within a robust sustainability-oriented waste management design framework. Ruiz-Vélez et al. [9] integrated SAW into transportation infrastructure decision-making, and Shahidin and Mohd Razif [10] applied it to warehouse route optimization. Trung et al. [11] further demonstrated its usefulness in engineering material selection. These applications show that SAW continues to be a practical ranking tool across diverse problem settings, especially when decision-makers require a method that is computationally simple and easy to communicate.

However, despite its practicality, SAW also has limitations. Its linear additive structure may oversimplify complex relationships among criteria, and its results are sensitive to weighting choices and normalization procedures. For this reason, more advanced decision-making approaches, such as fuzzy SAW, AHP, and fuzzy AHP, have been introduced to address uncertainty, vagueness, and subjective judgment in real-world decision-making. Nuriyev et al. [12] used fuzzy SAW and other fuzzy MCDM techniques in renewable energy transition analysis. Mhana and Awad [13] combined AHP, fuzzy AHP, GIS, and multi-criteria analysis in electric vehicle charging station siting. Mokhtariyan Sorkhan et al. [14] applied fuzzy AHP to evaluate indoor environmental quality, while Mohamed Nusaf and Kumaravel [15] integrated fuzzy AHP, entropy, and fuzzy VIKOR for polluted-region assessment. Wang and Su [16] employed an improved AHP model to analyze environmental pollution risk, and Zhang et al. [17] combined fuzzy comprehensive evaluation with PCA-AHP in ecological assessment. Additionally, Abdullah et al. [18] compared AHP and fuzzy AHP for solar power plant site selection. These studies indicate that contemporary ranking problems often require not only indicator aggregation but also mechanisms to reflect complexity and uncertainty in decision-making environments.

In parallel with MCDM methods, data envelopment analysis (DEA) has become one of the most established tools for evaluating the relative performance of decision-making units with multiple inputs and outputs. DEA is particularly valuable in policy and regional studies because it does not require a predefined production function and can accommodate a range of economic, operational, and environmental variables. Wu et al. [19], for example, used

DEA-Tobit analysis to examine the role of ICT in sustainable tourism performance. Huang et al. [20] applied a two-stage meta undesirable EBM model to study the impact of temperature on electricity consumption, air pollution, and GDP. He and Zhu [21] developed a dynamic two-stage slacks-based model with shared inputs for Chinese provincial industry systems, while Zhang, Zhao, and Zha [22] used a dynamic two-stage DEA model to evaluate regional industrial systems and pollution control. Halkos and Argyropoulou [23] analyzed the health impacts of air pollution through a two-stage DEA framework, and Moutinho and Madaleno [24] examined eco-efficiency in EU countries using two-stage DEA and fractional regression. Together, these studies demonstrate that DEA, particularly in two-stage form, has become a central methodology for understanding how economic and environmental processes are linked.

The methodological basis for two-stage DEA has been well established in the literature. Kao and Hwang [25] proposed a relational two-stage DEA model that makes it possible to decompose the efficiency of an overall system into stage-level efficiencies when intermediate products connect the stages. Chen et al. [26] later introduced an additive efficiency decomposition approach that determines overall efficiency as a weighted average of stage efficiencies. These foundational studies are especially important in contexts where production or performance is not generated in a single step but through linked processes. In regional sustainability analysis, this is highly relevant because initial economic and demographic conditions may first influence operational or industrial activity before shaping final environmental and economic outcomes.

Subsequent research has extended two-stage DEA into more complex decision settings. Liang et al. [27] introduced a game-theory perspective for two-stage DEA, allowing the interaction between stages to be interpreted through a leader–follower structure. Li et al. [28] further examined the question of stage dominance in two-stage network DEA, focusing on which stage acts as the leader in determining system performance. Anandarao et al. [29] applied efficiency decomposition in a two-stage DEA setting to life insurance companies, reinforcing the usefulness of stage-based analysis in real-world decision environments. These studies suggest that the structure of inter-stage relationships matters greatly when interpreting overall efficiency and that multi-stage analysis can reveal internal performance dynamics that remain hidden in conventional single-stage models. Recent informatics-oriented regional sustainability studies have also emphasized integrated DEA-based decision-support frameworks for Thai provincial benchmarking and sustainability evaluation [30].

The present study is conceptually related to that by Aungkulanon et al. (2025) [30], but it addresses a different methodological objective. While Aungkulanon et al. [30] developed an informatics-oriented framework that integrates twin mean-variance two-stage DEA with desirability-based decision analytics to evaluate both efficiency and stability in regional sustainability performance, the current study focuses on the upstream problem of representative province selection and the downstream problem of comparative efficiency benchmarking. Specifically, the present framework introduces AWVAA as a structured screening mechanism to identify representative provinces before applying CCR-based two-stage DEA and super-efficiency analysis for benchmarking. In this sense, the two studies are complementary rather than redundant: ref. [30] emphasizes joint efficiency–stability evaluation, whereas the current paper emphasizes screening transparency, representative unit selection, and benchmark-oriented efficiency assessment.

Although both MCDM and DEA have been widely applied in sustainability-oriented research, several important gaps remain. First, many studies focus either on ranking alternatives through weighted indicator aggregation or on estimating relative efficiency through DEA, but relatively few integrate the two into a unified analytical pipeline. In practice, however, efficiency analysis is often preceded by a screening problem: researchers must determine which units should be included in detailed analysis and how representative

balance should be maintained. Second, many regional sustainability studies focus on economic performance or environmental quality rather than assessing how both might be assessed together in a structured multi-stage framework. Third, even when two-stage DEA is utilized, the problem of picking representative decision-making units from a wider national context is not usually directly addressed. These constraints constrain the practical application of existing methodologies for policymakers who require transparent, verifiable, and regionally balanced evaluation systems.

This paper closes these gaps by integrating a structured screening approach with a two-stage efficiency assessment framework. The proposed additive weighting-based variant assessment algorithm (AWVAA) expands the SAW by adding global and local screening methods to preserve regional representation and to identify provinces with complete and relevant data. Then, this screening phase is connected to a two-stage DEA model that measures the transformation of initial economic inputs into intermediate operational factors and ultimate economic and environmental consequences by selected provinces. Thus, the contribution of the study should be seen not only in the application of existing methods but also in their integration into a cohesive decision-support framework for regional sustainability evaluation.

From an informatics point of view, this integration is essential because it considers sustainability evaluation as a systematic process of data selection, transformation, and interpretation, not as a single computing operation. The framework structures heterogeneous provincial data into a replicable analytical sequence conducive to benchmarking, comparison, and use in policy. By integrating multi-criteria screening and two-stage efficiency analysis, the study offers a clearer and more realistic framework for assessing the trade-off between economic production and environmental sustainability among Thai provinces.

Table 1 summarizes representative studies related to regional sustainability assessment, MCDM-based screening, and DEA-based performance evaluation. The reviewed literature shows that previous studies have made important contributions in three main areas. First, several studies have advanced environmental and regional efficiency assessment by applying DEA and two-stage DEA models to evaluate economic production, energy use, pollution control, and sustainability outcomes. Second, MCDM studies have contributed transparent ranking and selection procedures, particularly through SAW, AHP, fuzzy AHP, TOPSIS, VIKOR, and related methods. Third, recent informatics-oriented studies have emphasized the value of integrating heterogeneous data into reproducible decision-support frameworks for sustainability benchmarking. However, most existing studies apply MCDM or DEA as separate analytical tools. Limited attention has been given to the upstream problem of selecting representative and regionally balanced DMUs before conducting DEA-based benchmarking. In addition, few studies explicitly connect data-completeness screening, global and local MCDM-based representative unit selection, multi-normalization robustness, two-stage DEA evaluation, and policy interpretation within one coherent framework. This study addresses these gaps by integrating AWVAA-based representative province selection with CCR-based two-stage DEA and super-efficiency benchmarking for Thai provincial sustainability assessment.

As shown in Table 1, prior studies provide strong methodological foundations for sustainability assessment, MCDM-based ranking, and DEA-based efficiency evaluation. Nevertheless, the table also highlights a methodological gap in linking these components into a unified screening-and-benchmarking framework. Conventional MCDM studies generally focus on ranking alternatives, whereas DEA studies usually assume that the set of DMUs has already been defined. The present study contributes to the sustainability assessment literature by bridging these two stages. AWVAA is used to formalize representative province selection through data-completeness screening, global and local SAW-based eval-

uation, and intensive multi-normalization re-evaluation. The selected provinces are then evaluated using CCR-based two-stage DEA and super-efficiency analysis. Therefore, the contribution of this study lies not only in applying existing methods but in integrating them into a transparent informatics-oriented workflow for regional sustainability benchmarking and policy support.

Table 1. Representative studies on regional sustainability assessment, MCDM-based screening, DEA-based performance evaluation, and the methodological gap addressed by the present study.

Study	Application Focus	Analytical Approach	Key Contribution	Relevance to the Present Study
Wang et al. (2024) [1]	Urban environmental performance in China	Euclidean distance function	Examines the balance between economic production and environmental protection	Supports the need to jointly evaluate economic and environmental outcomes
Krmać and Djordjević (2024) [2]	Port environmental efficiency	One-stage and two-stage DEA	Compares single-stage and multi-stage efficiency structures	Shows the value of two-stage modeling for environmental performance analysis
Othman et al. (2023) [3]	Air pollutant performance in Malaysia	DEA, SBM, MPI, PCA	Integrates efficiency and environmental indicators in pollution-related analysis	Demonstrates the relevance of DEA for environmental assessment
Yang et al. (2023) [4]	Government investment in air pollution control	Three-stage DEA-Malmquist model	Evaluates public investment efficiency in pollution control	Supports the use of DEA in policy-oriented environmental evaluation
Zheng et al. (2023) [5]	Green energy efficiency and pollution reduction	Non-radial DEA	Assesses coordinated environmental and energy performance	Reinforces the importance of multi-output sustainability assessment
Ghaemi-Zadeh and Eghbali-Zarch (2024) [6]	Business strategy evaluation	D-CRITIC, fuzzy MULTI-MOORA, SAW, TOPSIS, VIKOR	Compares multiple ranking methods in a decision-making setting	Illustrates the continuing usefulness of SAW in structured screening
Wati et al. (2024) [7]	Socio-economic welfare evaluation	SAW, TOPSIS, MOORA	Compares alternative MCDM methods for ranking welfare performance	Supports the use of SAW as a transparent screening method
Tirkolaee et al. (2024) [8]	Sustainable waste management design	Robust optimization, weighted goal programming, SAW	Integrates MCDM into a sustainability-oriented planning framework	Shows that SAW can support complex sustainability decisions
Ruiz-Vélez et al. (2024) [9]	Sustainable transport infrastructure	NSGA-II, SAW, FUCA, LCA	Combines optimization and sustainability assessment methods	Highlights the role of multi-criteria screening in infrastructure decisions

Table 1. Cont.

Study	Application Focus	Analytical Approach	Key Contribution	Relevance to the Present Study
Shahidin and Mohd Razif (2024) [10]	Warehouse route optimization	Entropy, SAW, WFWA	Uses SAW for practical ranking and route selection	Supports SAW's interpretability in applied decision contexts
Trung et al. (2024) [11]	Engineering material selection	SAW, RAM, PIV, Entropy, LOPCOW	Applies SAW in technical selection and ranking problems	Confirms the flexibility of SAW across domains
Nuriyev et al. (2023) [12]	Renewable energy transition	Fuzzy SAW, fuzzy TOPSIS, fuzzy MOORA, fuzzy VIKOR	Incorporates uncertainty into MCDM-based energy planning	Shows extensions of weighting-based ranking under uncertain conditions
Mhana and Awad (2024) [13]	EV charging station siting	AHP, FAHP, GIS, MCDA	Integrates spatial analysis and multi-criteria decision tools	Relevant to regional and location-based sustainability assessment
Mokhtariyan Sorkhan et al. (2024) [14]	Indoor environmental quality	FAHP	Uses fuzzy prioritization for environmental quality evaluation	Demonstrates the use of weighted judgment in environmental studies
Mohamed Nusaf and Kumaravel (2024) [15]	Polluted region assessment	FAHP, Entropy, fuzzy VIKOR	Combines weighting and environmental risk evaluation	Supports multi-criteria approaches to environmental assessment
Wang and Su (2023) [16]	Environmental pollution risk	Improved AHP	Evaluates economic loss and financial risk from pollution	Links environmental quality with broader economic implications
Zhang et al. (2023) [17]	Ecological environment quality	Fuzzy evaluation, PCA-AHP	Integrates multiple indicators into ecological quality assessment	Relevant to composite regional sustainability measurement
Abdullah et al. (2021) [18]	Solar power plant site selection	AHP, Fuzzy AHP	Compares structured decision approaches for location selection	Supports multi-criteria screening logic in sustainability planning
Wu et al. (2024) [19]	Smart tourism sustainability	DEA-Tobit model	Examines sustainable destination performance using DEA	Shows DEA's usefulness in digital and sustainability contexts
Huang et al. (2024) [20]	GDP, temperature, and pollution	Two-stage meta undesirable EBM	Models economic and environmental interactions in a multi-stage structure	Supports the use of two-stage models for linked sustainability outcomes
He and Zhu (2023) [21]	Industrial pollution control	Dynamic two-stage SBM with shared inputs	Evaluates industrial systems with environmental carry-over effects	Reinforces the value of multi-stage DEA in pollution control
Zhang, Zhao, and Zha (2021) [22]	Regional industrial systems	Dynamic two-stage DEA	Assesses production and abatement efficiency jointly	Shows the importance of linked-stage efficiency analysis

Table 1. *Cont.*

Study	Application Focus	Analytical Approach	Key Contribution	Relevance to the Present Study
Halkos and Argyropoulou (2021) [23]	Energy use and air pollution health impacts	Modified multiplicative two-stage DEA	Connects energy, pollution, and health impacts through two-stage efficiency analysis	Closely related to joint economic-environmental assessment
Moutinho and Madaleno (2021) [24]	Eco-efficiency in EU countries	Two-stage DEA and fractional regression	Evaluates environmental and economic performance together	Supports two-stage DEA for regional sustainability studies
Kao and Hwang (2008) [25]	Two-stage efficiency decomposition	Relational two-stage DEA	Provides a foundation for decomposing system and stage efficiencies	Forms the theoretical basis for the two-stage DEA structure used here
Chen et al. (2009) [26]	Additive efficiency decomposition	Two-stage DEA	Defines overall efficiency as a weighted combination of stage efficiencies	Supports the interpretation of linked-stage performance
Liang et al. (2008) [27]	Two-stage DEA with game structure	DEA game approach	Models leader-follower relationships between stages	Relevant background for stage interaction, though not central in the revised paper
Li et al. (2018) [28]	Stage leadership in two-stage network DEA	Network DEA	Examines which stage dominates overall system performance	Provides context for inter-stage efficiency interpretation
Anandarao et al. (2019) [29]	Life insurance company performance	Two-stage DEA decomposition	Applies stage-based decomposition in practice	Demonstrates the practical use of two-stage efficiency analysis
Aungkulanon et al. (2025) [30]	Regional sustainability assessment in Thai provinces	Twin mean-variance two-stage DEA integrated with desirability-based decision analytics	Develops an informatics-oriented framework that evaluates both efficiency and stability in economic and environmental performance across regions	Demonstrates the growing use of informatics-driven DEA frameworks for Thai provincial sustainability benchmarking and supports the present study's emphasis on data-driven regional evaluation

3. Related Methods

This study develops an integrated analytical framework for evaluating provincial performance in Thailand under the dual objectives of economic production and environmental sustainability. From an informatics perspective, the methodological challenge lies in organizing heterogeneous regional data into a structured decision process that supports screening, comparison, and efficiency assessment. This difficulty is addressed by the suggested framework, which integrates an additive weighting-based variant assessment algorithm (AWVAA) with two-stage data envelopment analysis (TSDEA). AWVAA is used

to choose typical provinces from a larger national database, and TSDEA is used to determine how well the selected provinces convert initial inputs into intermediate operational factors and final economic and environmental results.

The whole system is structured as a sequential decision-support procedure. In the first step, the number of provinces is narrowed down to a representative set of decision-making units (DMUs) with acceptable data completeness and geographical balance by means of a multi-criteria screening approach. The second step evaluates the selected DMUs using a two-stage efficiency framework. This is a suitable set-up for provincial sustainability analysis because regional performance is not produced in one step. Initial economic and demographic conditions determine operational activity, which influences both economic output and environmental quality. The methodology disaggregates these steps analytically and provides a more transparent view of the performance of provinces across connected development processes.

The methodological structure employed in this investigation is summarized in Figure 1. This sets the stage for the relationship between the two key analytical components before they are discussed in depth. The first component is the AWVAA-based screening method, which uses MCDM and SAW to determine the representative provinces (D^*). The second component is the CCR-based two-stage DEA evaluation, which evaluates the selected provinces in terms of their economic and environmental performance. This overview is meant to explain the connection of the associated methodologies within the general framework of data-driven informatics.

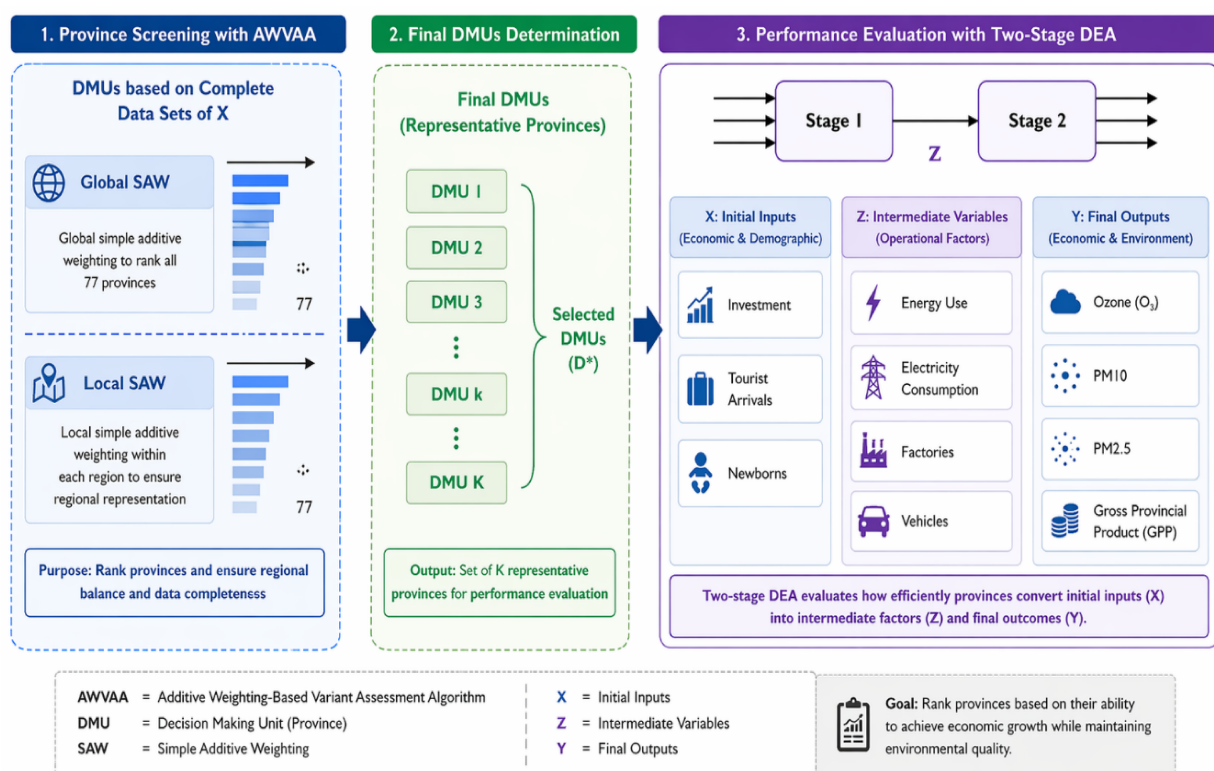


Figure 1. Overview of the proposed framework integrating AWVAA-based provincial screening with two-stage DEA for economic and environmental performance evaluation.

3.1. Simple Additive Weighting (SAW)

This study used simple additive weighting (SAW) as the first ranking method to filter the provinces. SAW is one of the most popular multi-criteria decision making approaches due to its simplicity, ease of implementation, and clear scoring scheme. Its fundamental advantage is that it enables the aggregation of many indicators with different scales into

a single composite score. This makes SAW appropriate for determining provinces with balanced performance based on chosen economic and environmental parameters before a more thorough efficiency study in the context of provincial evaluation.

In practice, SAW is conducted by assigning weights to the evaluation criteria and then computing the weighted score of each alternative after normalization. The obtained score indicates the relative position of each province in relation to the given criteria. The current study uses SAW as a screening tool and not as the final evaluation model. Its function is to systematically and reproducibly rank provinces in the first pass using variables such as investment, tourist arrivals, births, and environmental quality metrics, thereby ensuring that the provinces included in the second-stage study are not picked arbitrarily but through a clear data-driven method.

Another advantage of SAW is its interpretability. Because the scoring process is straightforward, it is easier for readers and policymakers to understand how provinces are filtered and ranked. This is particularly important in an informatics-oriented framework, where transparency and reproducibility are essential for decision support. Although SAW does not capture all complexities of interdependent regional systems, it provides a practical foundation for the structured selection of representative DMUs.

In the SAW procedure, each province is treated as an alternative and each evaluation indicator is treated as a criterion. Let x_{ij} denote the original value of province i under criterion j , where $i = 1, 2, \dots, n$ and $j = 1, 2, \dots, m$. Because the indicators are measured in different units, the raw values are first normalized into dimensionless scores. For benefit-type criteria, where a higher value is preferred, the normalized value is calculated as follows:

$$r_{ij} = \frac{x_{ij}}{\max_i x_{ij}}. \quad (1)$$

For cost-type criteria, where a lower value is preferred, the normalized value is calculated as follows:

$$r_{ij} = \frac{\min_i x_{ij}}{x_{ij}}. \quad (2)$$

The normalized values are then combined using additive weighting. The SAW score of province i is calculated as follows:

$$S_i = \sum_{j=1}^m w_j r_{ij} \quad (3)$$

where S_i is the composite or global SAW score of province i , r_{ij} is the normalized value of province i under criterion j , and w_j is the weight assigned to criterion j . The criterion weights satisfy the condition:

$$\sum_{j=1}^m w_j = 1, \quad w_j \geq 0. \quad (4)$$

In this study, equal weighting was used in the SAW-based screening stage because the purpose of AWVAA is representative province selection rather than preference-based prioritization. Equal weighting avoids imposing subjective priority among economic, demographic, and environmental indicators when no explicit stakeholder preference structure is available. Therefore, the weight of each criterion was calculated as follows:

$$w_j = \frac{1}{m}. \quad (5)$$

Economic and demographic indicators such as investment, tourist arrivals, and new-borns were treated as benefit-type criteria, while air pollution indicators such as ozone,

PM10, and PM2.5 were treated as cost-type criteria because lower pollution levels indicate better environmental performance. This weighting and normalization structure was applied consistently in the global and local SAW evaluations before the intensive multi-normalization re-evaluation step.

3.2. Additive Weighting-Based Variant Assessment Algorithm (AWVAA)

Based on existing multi-criteria decision-making (MCDM) theories, especially simple additive weighting (SAW), this study proposes a structured screening algorithm, the additive weighting-based variant assessment algorithm (AWVAA), to select the representative provinces before the two-stage DEA evaluation. It is not meant to replace normal MCDM methodologies or the typical SAW score formula. Rather, its novelty lies in organizing several MCDM-based and SAW-based components—including weighted additive scoring, global and local ranking, multiple normalization variants, and geometric-mean aggregation—into an integrated and reproducible province-screening protocol. This protocol addresses three practical limitations of conventional SAW-based ranking: dependence on a single global ranking, limited consideration of regional representation, and sensitivity to a single normalization procedure. The purpose of this integration is to support transparent, regionally balanced, and analytically suitable preselection of decision-making units (DMUs) before the CCR-based two-stage DEA analysis.

Conventional SAW applications usually normalize criteria, assign weights, aggregate the weighted scores, and then rank alternatives directly. This approach is useful when the purpose is to identify the best alternative under a single comparison structure. However, in provincial sustainability assessment, the objective is not only to rank provinces but also to select a representative and analytically suitable set of decision-making units (DMUs) for subsequent DEA benchmarking. A purely global SAW ranking may overrepresent economically dominant regions and exclude provinces that are important within their own regional context. Therefore, AWVAA extends the conventional SAW logic by combining global screening, local regional screening, and intensive global re-evaluation into a single algorithmic procedure.

In the present investigation, AWVAA comprises three methodological components. First, AWVAA utilizes a two-level screening framework that integrates global SAW ranking across all provinces and local SAW ranking inside regions. This allows the selected set of DMUs to represent nation-level performance and regional balance. Second, AWVAA uses an intense re-evaluation process based on numerous normalization approaches, namely, Van Delft and Nijkamp's normalization, Weitendorf's normalization, Jüttler and Körth's normalization, and Taguchi's signal-to-noise ratio. This lowers reliance on a single normalizing approach and improves the resilience of the final screening result. Third, AWVAA uses a geometric-mean aggregation to combine the results of multiple normalization variations into a single composite screening score. This makes the final choice less vulnerable to excessive values of any individual normalizing method.

Accordingly, AWVAA should be interpreted as a variant-assessment and representative-unit selection algorithm rather than as a standalone final-ranking method. Its role is to convert a heterogeneous national provincial dataset into a smaller, regionally balanced, and analytically suitable set of DMUs for two-stage DEA. This distinguishes AWVAA from existing SAW-based screening approaches, which commonly produce a direct ranking of alternatives but do not explicitly combine national ranking, regional balancing, multi-normalization robustness, and downstream DEA readiness into one integrated framework (Table 2).

Table 2. Methodological distinction between conventional SAW-based screening and the proposed AWVAA.

Component	Conventional SAW-Based Screening	Proposed AWVAA
Main purpose	Ranking alternatives based on weighted normalized scores	Selecting representative and DEA-ready DMUs from a heterogeneous provincial dataset
Comparison structure	Usually one global comparison across all alternatives	Combined global comparison and local regional comparison
Regional representation	Not explicitly considered	Explicitly incorporated through local SAW screening within regions
Normalization approach	Usually relies on one normalization method	Uses multiple normalization variants for intensive re-evaluation
Aggregation logic	Weighted summation of normalized criteria	Weighted scoring followed by geometric-mean aggregation across normalization variants
Final output	Ranked list of alternatives	Representative DMU set for subsequent CCR-based TSDEA benchmarking
Methodological contribution	Transparent and simple ranking	Integrated screening protocol linking data completeness, regional balance, normalization robustness, and DEA readiness

In this sense, AWVAA extends existing SAW-based approaches by shifting the methodological objective from simple ranking to structured representative unit selection. This is important for the present study because the quality and interpretability of the subsequent two-stage DEA analysis depend on the appropriateness of the selected DMUs. By formalizing the screening process before DEA, AWVAA improves transparency, reproducibility, and policy relevance in provincial sustainability benchmarking.

3.3. Two-Stage Data Envelopment Analysis (TSDEA)

After the representative provinces are selected, their performance is evaluated using two-stage data envelopment analysis. DEA is a non-parametric efficiency assessment technique that is well suited to problems involving multiple inputs and outputs. In regional sustainability studies, DEA is especially useful because it does not require the specification of a fixed production function and can therefore accommodate different forms of economic and environmental interaction.

A two-stage framework was chosen to reflect the sequential nature of provincial performance. In the first stage, provinces transform initial inputs such as investment, tourist arrivals, and newborns into operational and infrastructure conditions, represented by intermediate variables. The intermediate variables affect the economic and environmental results in the second stage. This division enables the model to capture how upstream regional features translate to downstream sustainability performance rather than treating all indicators as part of one undifferentiated process.

The first set of inputs in this analysis are investment, tourist arrivals, and babies. These indicators are indicative of the economic attractiveness, demographic dynamics, and development capability at the provincial level. The mediating factors are energy use, electricity consumption, factory counts, and vehicle numbers, which represent operational intensity and the structural conditions through which economic activity impacts sustainability results. The outputs are gross provincial product and air quality indices (ozone,

PM10 and PM2.5). The model uses these variables together to investigate how provinces balance economic development with environmental effects.

The two-stage DEA model based on CCR [31] is still the central analytical model in the new framework; it is a clear and defensible basis for the assessment of stage efficiency under constant returns to scale. This approach allows estimating the overall efficiency and the stage efficiency in a linked manufacturing structure. Super-efficiency analysis can be employed for further discrimination of performance among efficient units for the provinces on the efficiency border. Within this context, the super-efficiency ratings greater than one can be interpreted as performance beyond the conventional frontier and are utilized only for a more exact ranking of efficient provinces.

3.4. Data Normalization and Integrated Evaluation Logic

As the variables utilized in this study are measured in different units and magnitudes, normalization is necessary for a meaningful comparison and aggregate. Normalization is used in the screening stage to put disparate indications into comparable scales for the SAW-based ranking methods. In the efficiency stage, normalization contributes to stability when comparing provinces based on economic and environmental dimensions. This is particularly important if the research incorporates financial, demographic, operational, and pollution-related factors within a single framework.

The entire logic of the procedure may thus be stated in the following three-part analytical sequence. First, we identify provinces with comprehensive and relevant data. Second, AWVAA is used to screen and select a representative collection of DMUs via global and local SAW methods. Third, CCR-based two-stage DEA is applied to assess the efficiency of selected provinces in converting initial inputs into intermediate operational factors and final sustainability outcomes. This structure is incorporated, providing the framework with a decision-support orientation rather than only a technical optimization effort.

The methodological contribution of this study is not based on the proposition of a new DEA theory. However, its contribution is to integrate multi-criteria screening and two-stage efficiency evaluation into a coherent framework for provincial sustainability assessment. This is a crucial distinction. Most existing studies use either ranking methods or DEA models individually, and there is little research that directly links the selection of representative units to the subsequent modeling of their multi-stage performance. The AWVAA component of this paper enhances the transparency of province selection, and the two-stage DEA component offers a systematic approach to interpret the associated economic and environmental performance.

4. The Proposed Data-Driven Informatics Framework

This paper presents a data-driven informatics framework to evaluate provincial performance in Thailand under the dual objectives of economic output and environmental sustainability. The framework combines an additive weighting-based variant assessment algorithm (AWVAA) with a CCR-based two-stage data envelopment analysis (TSDEA) model. The goal is to transform a large and heterogeneous provincial dataset into a structured decision-support process that allows for representative unit selection, multi-stage efficiency evaluation, and policy-relevant interpretation. This framework does not simply apply a direct efficiency model across all the available provinces. Instead, it first selects a representative sample of decision-making units (DMUs) and then assesses the efficiency with which these units turn the initial development conditions into the intermediate operational factors and the final economic and environmental results.

The suggested framework works in two intertwined analytical processes. First, AWVAA is utilized as a structured province-screening tool to limit the national dataset to a balanced and analytically manageable subset of representative DMUs. Second, a relational CCR-based two-stage DEA model is used to analyze the selected provinces. This second stage provides an estimate of overall efficiency and allows for further stage-specific interpretation within the provincial development process. Figure 2 demonstrates the conceptual workflow of the proposed data-driven informatics system combining provincial screening through AWVAA, CCR-based two-stage DEA evaluation, and policy interpretation.

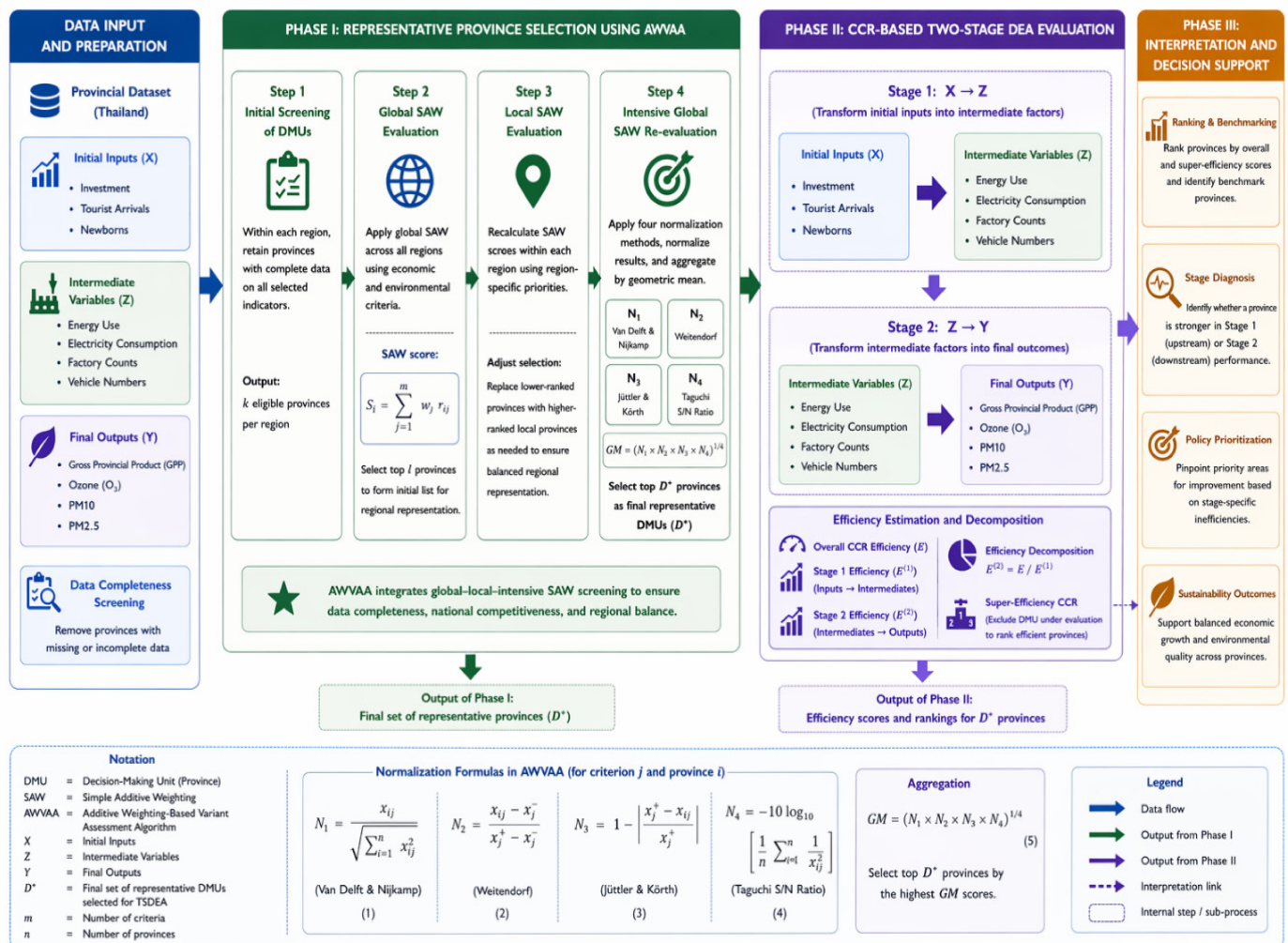


Figure 2. Conceptual workflow of the proposed data-driven informatics framework for provincial sustainability assessment.

4.1. AWVAA-Based Screening of Representative Provinces

A structured multi-step screening technique is proposed in the form of the additive weighting based variant assessment algorithm (AWVAA) to select representative DMUs from the provincial dataset. The algorithm relies on the logic of simple additive weighting (SAW) and its variants to allow a transparent and balanced preselection procedure before the two-stage DEA evaluation. The major aim is to reduce the collection of provinces to a subset that is analytically tractable, geographically balanced, and sufficiently robust to allow thorough performance assessment. In the present study, AWVAA is used as the initial layer of the informatics framework to convert a huge and diverse dataset into a smaller and more similar set of provinces for efficiency analysis.

The AWVAA technique includes four consecutive steps, i.e., initial screening of DMUs, global SAW evaluation, local SAW evaluation, and intensive global SAW re-evaluation. These methods ensure that provinces are not chosen according to a single national ranking but rather according to both overall performance and regional representation. This is significant since a strictly global rating may over-represent some regions and exclude provinces that do well within their own regional setting.

The first stage consists of screening the DMUs. The first step is to identify provinces with complete input and output data for the selected variables. This screening is completed for each region to guarantee adequately extensive and reliable observations for economic and environmental analysis of all qualifying DMUs. Let k be the number of provinces in each area that meet the data-completeness condition. Only these provinces are retained as candidate DMUs for the next stage of AWVAA. This phase is important since the succeeding two-stage DEA model requires a detailed specification of inputs, intermediate variables, and outcomes. If there were missing or partial observations for provinces, the comparison analysis would be compromised.

Then the second stage, i.e., global SAW evaluation, is initiated. After identifying the qualifying provinces, all regions are subjected to the global SAW procedure. At this point, a composite score based on a weighted aggregate of the selected performance indicators is assigned to each province. The indicators include economic and demographic data, like investment, tourist arrivals, and newborns, and environmental indicators, like ozone, PM10, and PM2.5. The aim is to construct a first national ranking of provinces using the overall balance of economic and environmental performance. The provinces with the highest ratings on these indicators are selected to construct a preliminary list of representative candidates. Let l be the predefined number of provinces to be picked at this stage in order to have a wide representation throughout all the regions.

The final step is local evaluation by SAW. Then, a local SAW operation is performed in each location to refine the initial selection and to maintain geographical diversity. At this level, candidate provinces are re-ranked by comparison within the area. The goal is for each region to contribute an equitable quota of representative provinces to the final DMU set. Lower-performing provinces on the original global list are substituted with strong regional performers as needed. This modification enhances the regional balance and decreases the risk of a final DMU set being dominated by a few economically stronger regions. This local SAW phase is significant from a decision-support perspective because it preserves regional variability while providing analytical rigor.

Before applying the four normalization metrics, all criteria are harmonized into the same preference direction. This is necessary because ozone, PM10, and PM2.5 are cost-type environmental indicators, where lower values indicate better performance. As described earlier, these variables are first transformed into benefit-oriented environmental performance scores using a lower-the-better desirability function. Therefore, the benefit-linked normalization metrics are not applied to raw cost criteria but to a transformed performance matrix in which higher values consistently represent better performance. This procedure avoids rewarding higher pollution values and ensures that economic, demographic, and environmental indicators are comparable under the same higher-is-better interpretation.

The fourth step is the intensive global SAW re-evaluation. After balancing provinces through the global and local SAW stages, an intensive global re-evaluation is performed to determine the final set of representative DMUs for the two-stage DEA analysis. This final step applies several normalization techniques to improve the comparability and robustness of the rankings. Specifically, four normalization methods are used: Van Delft and Nijkamp's normalization (N_1), Weitendorf's normalization (N_2), Jüttler and Körth's normalization (N_3), and Taguchi's signal-to-noise ratio (N_4). Let x_{ij} denote the value of province i under

criterion j , while x_j^+ and x_j^- denote the maximum and minimum values observed for criterion j , respectively. The normalization expressions are defined as follows:

$$N_1 = \frac{x_{ij}}{\sqrt{\sum_{i=1}^n x_{ij}^2}}; \quad (6)$$

$$N_2 = \frac{x_{ij} - x_j^-}{x_j^+ - x_j^-} \quad (7)$$

$$N_3 = 1 - \frac{|x_j^+ - x_{ij}|}{x_j^+} \quad (8)$$

$$N_4 = -10 \log_{10} \left[\frac{1}{n} \sum_{i=1}^n \frac{1}{x_{ij}^2} \right] \quad (9)$$

In the intensive global re-evaluation step, the application of several normalizing procedures is designed to lessen the dependence on a single scaling rule and to improve the robustness of the AWVAA-based screening process. In a typical SAW-based assessment, normalization is not a neutral technical step since the final ranking can be sensitive to the choice of transformation method. Different normalization metrics might emphasize relative distance, proportional change, vector-based scaling, or dispersion in different ways. This issue is particularly critical in the case of sustainability evaluation in a province because the indicators vary widely in magnitude, unit, and distribution, ranging from economic and demographic factors to environmental air quality assessments. Economic and demographic indicators can have very skewed distributions. Air pollution indicators (e.g., ozone, PM10, and PM2.5) have a reversed interpretation, since lower values imply better environmental performance. Thus, employing different normalization measures controls the sensitivity of the procedure before the final choice of representative provinces.

The four normalization metrics were selected because they represent commonly used but conceptually different transformation logics in MCDM-based assessment [32]. Van Delft and Nijkamp's normalization emphasizes relative performance with respect to the observed upper and lower bounds and is useful for identifying each province's relative position within the full performance range. Weitendorf's normalization provides a transparent range-based linear transformation that improves comparability across criteria measured in different units. Jüttler and Körch's normalization provides an alternative scaling structure that reduces reliance on a single min-max or distance-based formulation. Taguchi's signal-to-noise ratio was included because it introduces a robustness-oriented perspective by considering the stability and desirability of performance rather than only the normalized magnitude of each criterion. Together, these metrics allow the intensive global evaluation to capture different aspects of relative performance and reduce the possibility that the final selection is driven by only one normalization assumption.

This multi-normalization strategy was chosen instead of relying on a single normalization method because the objective of AWVAA is not merely to rank provinces but to select representative and DEA-ready decision-making units from heterogeneous provincial data. A single normalization metric can give rankings that are partially determined by its own scaling assumptions, particularly when the indicators have various units, ranges, and variability. For example, range-based approaches are straightforward to read but may be sensitive to extreme minimum or maximum values, whereas vector or distance-oriented transformations may preserve proportional connections but may also be influenced by highly skewed distributions. The second stage of intensive global evaluation increases the stability, transparency, and interpretability of the final AWVAA score by applying a set of

normalization options and aggregating their results. This decreases the possibility that the selected provinces are artefacts of a particular transformation rule.

The geometric mean was utilized to aggregate the normalized variant scores, as it provides a less compensatory aggregating technique than the arithmetic mean. Arithmetic aggregation means that a very high value under one normalization scheme can be countered by low performance under another. Instead, the geometric mean promotes provinces that are consistent across normalization variants and punishes very lopsided results. This quality is desirable in principle in the selection of representative units because a province should not be preserved only because it does very well under one normalization rule but poorly under others. It is also compatible with positive normalized scores and allows for multiplicative synthesis of various normalized assessment types. A minor positive modification was applied to the normalized scores, if necessary, to maintain strictly positive scores prior to geometric-mean aggregation and ensure computational validity. Therefore, the intensive global evaluation step improves the AWVAA-based screening procedure by merging different normalization views while highlighting the consistency between the normalized scores obtained.

After the four normalized scores are obtained, they are aggregated using the geometric mean:

$$GM = (N_1 \times N_2 \times N_3 \times N_4)^{1/4} \quad (10)$$

The composite score for extensive SAW re-evaluation is the geometric mean. The final representative set (denoted by *GM*) is comprises the provinces with the highest aggregate values and is then passed to the CCR-based two-stage DEA evaluation. We chose the geometric mean rather than the arithmetic or weighted mean since the goal of the rigorous global evaluation is to find provinces that are performing consistently on multiple normalization indicators. Because the arithmetic mean is compensable, a very strong score under one normalization criteria can compensate for weak scores under other metrics. In the absence of a strong theoretical or stakeholder-based rationale for weighting the value of each normalization indicator, a simple unweighted mean may be more acceptable. However, four normalization measures were utilized in this work as complementary robustness tests instead of preference weighted criteria. Hence, weighting them differently would impose an additional subjective assumption.

The geometric mean is better suited in this scenario since it represents a multiplicative type of aggregation that favors balanced performance across the normalization criteria and penalizes inconsistent or excessive outcomes. This attribute supports the aim of AWVAA in not only ranking the provinces but also in selecting representative and DEA-ready DMUs whose performance does not depend on one specific normalization rule. All normalized scores must be positive before the geometric mean can be taken; hence, a modest positive correction was applied where necessary to avoid zero or undefined results. Table 3 presents the explanations for the normalization metrics chosen for the intensive global review. The criteria were selected to represent multiple scaling viewpoints and to limit the possibility that the final AWVAA ranking would be sensitive to a particular normalization assumption.

Overall, AWVAA functions as a structured and reproducible preselection mechanism within the proposed informatics framework. It combines national comparison, regional balancing, and normalization-based refinement to identify representative provinces for detailed efficiency assessment. In methodological terms, AWVAA strengthens the transparency of unit selection and reduces arbitrariness in determining which provinces are included in the formal efficiency stage.

Table 3. Rationale for the normalization metrics used in the intensive global evaluation.

Normalization Metric	Normalization Metric	Normalization Metric	Normalization Metric
Van Delft and Nijkamp's metric	Relative position between observed best and worst values	Captures each province's relative standing within the full performance range	Useful for comparing alternatives against observed bounds
Weitendorf's metric	Linear range-based scaling	Provides a transparent and interpretable MCDM normalization structure	Supports comparability across criteria measured in different units
Jüttler and Körth's metric	Alternative range-based normalization	Reduces dependence on a single min–max transformation	Adds robustness to the screening process
Vector normalization metric	Rescaling by the Euclidean norm of alternatives under each criterion	Preserves proportional relationships while removing measurement scale effects	Useful for criteria with different magnitudes, but applied with other metrics to reduce sensitivity to extreme values
Geometric mean aggregation	Multiplicative synthesis of normalized metric scores	Combines multiple normalization results into a final composite score	Rewards consistency across metrics and reduces excessive compensation

4.2. CCR-Based Two-Stage DEA Evaluation

After the sample provinces are chosen, a relational two-stage DEA model based on CCR is employed to assess their performance. The two-stage structure is suitable since province sustainability performance is the result of related activities, not a single input–output relationship. The first stage involves the transformation of initial economic and demographic variables into intermediate operational factors by provinces. In the second step, these intermediate factors affect the final economic and environmental effects. The structure shows the logic that operational intensity is a function of the development conditions and that this, in turn, impacts the economic productivity and the quality of the environment.

The CCR model was used since the purpose of this study was to evaluate provincial performance within a shared proportional-efficiency frontier. In this approach, provinces are compared based on their relative capacity to convert development inputs into intermediate operational factors and into ultimate economic and environmental outputs. The CCR assumption is suited for this benchmarking purpose since it measures the whole technical efficiency under a shared production structure and facilitates proportional comparison among the selected typical DMUs.

The Banker–Charnes–Cooper (BCC) model [33] is often employed under the assumption of variable returns to scale, but the BCC model was not used as the main model in this study for two reasons. First, the objective of the present framework was not to separate pure technical efficiency and scale efficiency but to build a shared baseline for representative province sustainability performance. Secondly, the final DEA sample comprises 16 selected provinces with numerous inputs, intermediate variables, and outputs. In this case, the BCC model may lose discriminatory power since the extra convexity constraint can categorize more DMUs as efficient, especially when the number of variables is large relative to the number of DMUs. The CCR model, therefore, offers a more conservative and interpretable framework for comparative benchmarking in the present empirical scenario.

The selection of inputs, intermediate variables, and outcomes was based on the sequential logic of regional sustainability performance (Table 4). The initial inputs in a two-stage DEA should capture the developmental resources or conditions that are available

to each province, the intermediate variables should represent the operational and economic activities that are produced with these resources, and the final outputs should reflect the sustainability outcomes that result. Thus, investment, tourist arrivals, and newborns were chosen as the starting inputs, as these are three primary sources of provincial development pressure and capacity: capital formation, economic activity connected with mobility and consumption, and demographic demand. These contribute to the upstream conditions that influence the nature of provincial production systems and resource consumption.

Table 4. Theoretical justification for variables used in the CCR-based two-stage DEA model.

DEA Role	Variable	Theoretical Meaning	Justification
Initial input	Investment	Capital and development resource	Represents financial capacity supporting provincial economic activity
Initial input	Tourist arrivals	Economic mobility and service demand	Captures tourism-related activity, consumption, and pressure on local systems
Initial input	Newborns	Demographic demand	Reflects population dynamics and future service/resource demand
Intermediate	Energy use	Resource consumption intensity	Represents operational activity generated by development inputs
Intermediate	Electricity consumption	Production and service intensity	Captures electricity-dependent economic and urban activity
Intermediate	Factory counts	Industrial concentration	Reflects manufacturing and industrial operating structure
Intermediate	Vehicle numbers	Transportation intensity	Captures mobility, logistics activity, and transport-related pressure
Final output	GPP	Desirable economic outcome	Represents provincial economic production
Final output	Ozone	Environmental air quality outcome	Reflects air pollution condition associated with development activity
Final output	PM10	Environmental air-quality outcome	Captures particulate pollution and environmental burden
Final output	PM2.5	Environmental air quality outcome	Captures fine particulate pollution relevant to sustainability and public health

The intermediate variables examined were energy use, power consumption, number of factories, and number of vehicles. These variables describe the intensity of operations and how development inputs are transformed into economic and environmental outputs. These variables capture major mechanisms of provincial activity: energy consumption, electricity-dependent production and services, industrial concentration, and transportation intensity. They are seen as intermediate elements instead of final policy results of sustainability assessment. Rather, they are the pathways of activity that link development conditions to final economic productivity and environmental quality.

The last outcomes were gross provincial product (GPP), ozone, PM10, and PM2.5, which illustrate the dual aims of provincial sustainability, i.e., economic production and environmental performance. GPP reflects the desirable economic outcome from provincial growth, while air quality indices reflect adverse environmental implications connected

with industrial activity, energy use, transportation, and urbanization. In the DEA formulation, pollution indicators were considered in an environmental performance orientation, where a lower pollution level implies higher sustainability performance. This input–intermediate–output structure is conceptually consistent with a two-stage perspective of regional development, in which the first stage of provincial resources generates operational intensity and the second stage results in economic advantages and environmental impacts.

In this study, the initial inputs (X) include investment, tourist arrivals, and newborns. These variables reflect development potential, economic attractiveness, and demographic conditions at the provincial level. The intermediate variables (Z) are energy use, electricity consumption, factory counts, and vehicle numbers, which represent operational and infrastructural intensity. The final outputs are gross provincial product (GPP) and desirability-transformed air quality performance indicators derived from ozone (O_3), PM10, and PM2.5, where higher transformed values represent better environmental performance.

Because ozone, PM10, and PM2.5 are undesirable environmental indicators, they were not directly entered into the DEA model as raw desirable outputs. Instead, these variables were first transformed into desirable environmental performance scores using a lower-the-better desirability function. Let b_{ij} denote the original value of pollutant j for province i , where lower values indicate better environmental performance. The desirability-transformed value d_{ij} is defined as follows:

$$d_{ij} = \begin{cases} 1, & b_{ij} \leq L_j, \\ \left(\frac{U_j - b_{ij}}{U_j - L_j} \right)^{s_j}, & L_j < b_{ij} < U_j, \\ 0, & b_{ij} \geq U_j, \end{cases} \quad (11)$$

where L_j represents the lower or most desirable reference value, U_j represents the upper or least desirable reference value, and s_j is the shape parameter controlling the strictness of the desirability transformation. In this study, the lower-the-better desirability function converts each pollution indicator into a desirable environmental performance output, where a higher transformed value indicates better air-quality performance. Thus, lower ozone, PM10, and PM2.5 values receive higher desirability scores, while higher pollution values receive lower desirability scores.

To ensure compatibility with the DEA model, the transformed desirability scores were used as the final environmental outputs together with GPP. Therefore, the final output set consisted of GPP and the desirability-transformed air quality indicators for ozone, PM10, and PM2.5. This procedure preserves the standard DEA output orientation because all final outputs are expressed in a higher-is-better direction before the CCR-based two-stage DEA analysis.

Let x_{ij} denote input i for DMU j , z_{pj} denote intermediate variable p for DMU j , and y_{rj} denote final output r for DMU j . If there are m initial inputs, q intermediate variables, s final outputs, and n selected provinces, the overall efficiency of DMU k under the relational CCR two-stage structure is determined by:

$$E_k = \max \sum_{r=1}^s u_r y_{rk} \quad (12)$$

subject to the following conditions:

$$\sum_{p=1}^q w_p z_{pj} - \sum_{i=1}^m v_i x_{ij} \leq 0, j = 1, \dots, n \quad (12a)$$

$$\sum_{r=1}^s u_r y_{rj} - \sum_{p=1}^q w_p z_{pj} \leq 0, j = 1, \dots, n \quad (12b)$$

$$\sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \leq 0, j = 1, \dots, n \quad (12c)$$

$$\sum_{i=1}^m v_i x_{ik} = 1 \quad (12d)$$

$$u_r, v_i, w_p \geq \varepsilon \quad (12e)$$

where u_r , v_i , and w_p are the output, input, and intermediate weights, respectively, and ε is a small positive constant to prevent zero weights. This formulation estimates overall efficiency while preserving the internal linkage between the two stages.

To better interpret internal performance, the overall efficiency can be decomposed into stage-specific efficiencies. The first-stage efficiency reflects how effectively provinces convert initial inputs into intermediate operational factors, while the second-stage efficiency reflects how effectively those intermediate factors are translated into final economic and environmental outcomes. The first-stage efficiency for DMU k is expressed as follows:

$$E_k^{(1)} = \max \sum_{p=1}^q w_p z_{pk} \quad (13)$$

subject to the same relational constraints, and the second-stage efficiency is obtained as follows:

$$E_k^{(2)} = \frac{E_k}{E_k^{(1)}} \quad (14)$$

This decomposition is analytically useful, as it distinguishes between provinces that are relatively strong in terms of upstream operational formation and those that are stronger in terms of downstream sustainability conversion. Therefore, some provinces with identical total efficiency scores may have large differences in the location of their strengths and weaknesses in the two-stage process.

CCR super-efficiency analysis is conducted for provinces on the efficiency frontier to separate the efficient units. In this case, the analyzed DMU is omitted from the reference set and efficient provinces receive scores greater than one. These numbers are not considered as errors but rather as values signifying performance over the frontier defined by the other peer provinces and are used only to rank efficient provinces in a more accurate way. This is particularly beneficial when there are several provinces with efficiency ratings near to or equal to the conventional border value.

4.3. CCR Super-Efficiency Extension for Ranking Efficient Provinces

Although the relational CCR two-stage DEA model provides the main efficiency evaluation framework, it does not fully discriminate among provinces located on or near the efficiency frontier. To obtain a clearer ranking among efficient decision-making units (DMUs), this study additionally applies a super-efficiency CCR model as a supplementary ranking tool. The purpose of this extension is not to replace the main relational two-stage evaluation but to provide additional discrimination among provinces whose overall CCR efficiency is equal or close to unity.

Let x_{ij} denote input i for DMU j , and y_{rj} denote output r for DMU j . For the k -th DMU under evaluation, the super-efficiency CCR model excludes DMU k from the reference set and is formulated as follows:

$$\min \theta_k^{SE} \quad (15)$$

subject to the conditions:

$$\sum_{\substack{j=1 \\ j \neq k}}^n \lambda_j x_{ij} \leq \theta_k^{SE} x_{ik}, i = 1, 2, \dots, m \quad (15a)$$

$$\sum_{\substack{j=1 \\ j \neq k}}^n \lambda_j y_{rj} \geq y_{rk}, r = 1, 2, \dots, s \quad (15b)$$

$$\lambda_j \geq 0, j = 1, 2, \dots, n, j \neq k \quad (15c)$$

where θ_k^{SE} is the super-efficiency score of DMU k , and λ_j represents the intensity variable associated with peer DMUs. Because the evaluated DMU is removed from the reference set, efficient provinces may obtain super-efficiency values greater than 1.0. In this study, such values are interpreted as indicating performance beyond the frontier formed by the remaining peer provinces and are used only for ranking efficient provinces more precisely.

In interpreting the CCR super-efficiency results, values greater than 1.00 are expected for provinces that remain strong performers when evaluated against the frontier formed by the remaining peer provinces. These values should not be interpreted as absolute sustainability scores or probabilities. Rather, they serve as relative benchmarking indices that provide additional discrimination among efficient or near-frontier DMUs. Overall CCR efficiency remains the primary measure of comparative performance, while CCR super-efficiency is used as a supplementary ranking tool to distinguish provinces with similar or frontier-level efficiency performance.

Within the proposed framework, the super-efficiency CCR model is applied after the main relational CCR-based evaluation. Overall CCR efficiency remains the primary measure of comparative performance, while CCR super-efficiency is used as a secondary discrimination tool to order provinces that are efficient or nearly efficient under the common frontier. This distinction is important because it preserves the central role of the relational two-stage DEA structure while improving the interpretability of benchmarking results.

Accordingly, the analytical sequence in this study is as follows. First, AWVAA is used to screen and select representative provinces. Second, the selected provinces are evaluated using the relational CCR two-stage DEA model. Third, CCR super-efficiency is applied as an auxiliary ranking extension to distinguish among frontier provinces. This combination allows the framework to support both representative unit selection and more informative comparative benchmarking.

4.4. Analytical Workflow and Interpretation Logic

The overall framework can be summarized as a sequential analytical process. First, provincial data are collected and screened for completeness. Second, AWVAA is applied to identify a representative set of provinces through global and local SAW-based screening. Third, the selected provinces are evaluated using the relational CCR-based two-stage DEA model. Fourth, overall efficiency results are interpreted together with AWVAA screening outcomes to support comparative benchmarking and policy interpretation. Finally, super-efficiency analysis is used to rank the provinces located on the efficiency frontier. From an informatics perspective, the main value of this workflow lies in its ability to organize heterogeneous provincial data into a reproducible decision-support structure. The framework is not only meant to compute performance scores but also to connect data preparation, representative unit selection, multi-stage evaluation, and policy interpretation in one integrated analytical process. In this manner, the suggested framework acts as a bridge between raw provincial statistics and evidence-based regional assessment.

Thus the framework makes two interrelated contributions. First, it increases the transparency of province selection by explicitly formalizing the screening logic through AWVAA rather than considering unit selection as an informal preprocessing step. Second, it enhances interpretability by integrating representative unit screening with global CCR efficiency and super-efficiency benchmarking, while stage-level interpretation remains an auxiliary analytical approach. This linked structure provides a more policy-relevant basis for provincial benchmarking than a single-stage direct efficiency evaluation or a stand-alone ranking technique.

5. Results and Discussion

AWVAA-based screening and two-stage DEA analysis based on CCR were conducted in MATLAB R2024b. Data preparation, normalization, AWVAA score calculation, geometric-mean aggregation, and result visualization were performed using bespoke MATLAB programs. The DEA models were cast as linear programming problems and solved using the Optimization Toolbox in Matlab. In the DEA calculation, each of the selected provinces was handled separately under the common boundary determined by the representative DMU set. The overall efficiency scores were obtained by running the relational CCR-based two-stage DEA model, and the super-efficiency CCR model was run by removing the DMU under evaluation from the reference set. The lower-bound weight parameter was set to a tiny positive value to avoid zero weights. All input, intermediate, and output variables were preserved in double-precision format. The dual-simplex technique was used to solve the linear programs with the solver display turned off.

Numerical stability was ensured by setting the optimality and feasibility tolerances. There was no stochastic initialization, therefore the findings are deterministic and reproducible given the same dataset, the same normalization processes, and the same model settings. The computational workflow includes four main steps: (1) screening the provinces with complete data, (2) computing the global and local SAW-based AWVAA scores, (3) identifying the representative DMUs through intensive normalization-based re-evaluation, and (4) solving the CCR-based two-stage DEA and super-efficiency CCR models. This implementation structure allows the same provincial dataset and parameter settings to reproduce the whole study.

5.1. Results of AWVAA-Based Screening of Representative Provinces

The empirical study started with the implementation of the AWVAA-based screening approach to choose a representative set of provinces for in-depth efficiency assessment. Following the proposed data-driven informatics paradigm, the first step was to verify the completeness of the provincial dataset with respect to the selected initial inputs, intermediate variables, and final outputs. Only those provinces with complete observations of all variables were preserved as suitable candidate DMUs for the next SAW-based screening phases. This initial filtering step was important to guarantee the analytical consistency of the relational CCR-based two-stage DEA model.

The global SAW technique was used to evaluate the candidate provinces after screening for data completeness. At this step, the provinces were rated with a weighted aggregate of economic and environmental parameters including investment, tourist arrivals, births, and air-quality-related variables. The worldwide SAW assessment aimed to identify reasonably high-performing provinces from a national perspective and generate a first list of representative candidates.

This first national rating was then revised by the local SAW review in each geographical location. The local screening phase guaranteed that not only the most dominant provinces at the national level were selected; it retained regional balance by keeping high-

performing provinces in their particular regional contexts. This improvement increased the representativeness of the DMU set and made the screening method consistent with the more general benchmarking goal of the study.

Finally, the intensive global SAW re-evaluation was conducted using multiple normalization techniques and geometric-mean aggregation in order to determine the final representative set of provinces. This final step strengthened the robustness of the screening process and reduced dependence on a single normalization scheme. As a result, 16 provinces were selected as the final representative DMUs, denoted by D^* , for the CCR-based two-stage DEA evaluation. These selected provinces included Bangkok, Chonburi, Rayong, Ayutthaya, Nakhon Ratchasima, Chiang Mai, Chachoengsao, Phuket, Samut Prakan, Songkhla, Kanchanaburi, Pathum Thani, Khon Kaen, Ratchaburi, Samut Sakhon, and Saraburi. Table 5 presents the representative provinces identified through the AWVAA-based screening process.

Table 5. Representative provinces selected via the AWVAA-based screening procedure.

DMU	Province	Region	AWVAA Score
1	Bangkok	Central	39.5049
2	Chonburi	Eastern	21.8479
3	Rayong	Eastern	6.9520
4	Ayutthaya	Central	0.4293
5	Nakhon Ratchasima	Northeastern	0.3873
6	Chiang Mai	Northern	0.1843
7	Chachoengsao	Eastern	0.1825
8	Phuket	Southern	0.1818
9	Samut Prakan	Central	0.1236
10	Songkhla	Southern	0.1223
11	Kanchanaburi	Western	0.0798
12	Pathum Thani	Central	0.0584
13	Khon Kaen	Northeastern	0.0383
14	Ratchaburi	Western	0.0375
15	Samut Sakhon	Central	0.0256
16	Saraburi	Central	0.0219

Bangkok had the highest AWVAA score due to its screening-stage prominence among the selected provinces. As the national capital and largest metropolitan economy, Bangkok has a dominant profile in economic scale, development intensity, population concentration, and data completeness. These factors significantly influenced the MCDM/SAW-based screening process and are the reason for its significantly higher score in the AWVAA-based screening procedure compared to other provinces. This conclusion should, however, be viewed as indicative of prominence, not of DEA-derived efficiency. The AWVAA score measures the appropriateness and significance of a province to be included in the representative DMU set, whereas the CCR-based DEA stage measures the efficiency of the selected provinces in transforming inputs to intermediate factors and ultimate economic and environmental consequences. Therefore, the highest AWVAA score for Bangkok does not necessarily suggest that Bangkok is the most efficient province. Rather, it affirms that Bangkok is a very significant and necessary reference unit for further benchmarking.

5.2. Results of CCR-Based Two-Stage DEA Evaluation

Following the AWVAA-based screening phase, the selected representative provinces were evaluated using the relational CCR-based two-stage DEA model. In line with the framework described in Section 4, the two-stage structure was used to evaluate provincial performance as a linked process rather than a single aggregated input–output relationship.

In the first stage, the model assessed how effectively each province transformed the initial inputs—investment, tourist arrivals, and newborns—into intermediate operational factors, namely energy use, electricity consumption, factory counts, and vehicle numbers. In the second stage, the model evaluated how effectively these intermediate operational factors were translated into final economic and environmental outcomes, represented by gross provincial product (GPP), ozone (O₃), PM10, and PM2.5.

This relational structure produced three related results: overall CCR efficiency, stage-specific efficiency, and CCR super-efficiency for frontier ranking. Overall CCR efficiency represents the performance of each province in the whole two-stage framework. Stage-specific efficiency distinguishes between upstream efficiency in the transformation of initial inputs into intermediate factors and downstream efficiency in the transformation of intermediate factors into final outcomes. CCR super-efficiency was applied to further discriminate among provinces lying on the efficiency frontier.

The findings show significant differences among the provinces examined. All 16 provinces completed the AWVAA-based screening process and so represented relatively strong and regionally balanced candidates; nonetheless, the CCR-based two-stage DEA evaluation revealed considerable disparities in efficiency. This demonstrates that the screening procedure selected representative provinces but did not eliminate considerable heterogeneity in how these provinces balanced development circumstances, operational intensity, and final sustainability outcomes. Table 6 shows the main CCR-based efficiency results for the chosen provinces, and Figure 3 presents a graphical representation of their overall CCR efficiency and super-efficiency rankings.

The results in Table 6 have important benchmarking implications. First, the selected provinces show clear variations in relative efficiency, even though all were identified as representative DMUs through the AWVAA-based screening process. Phuket, Samut Sakhon, and Rayong achieved overall CCR efficiency scores of 1.0000, indicating that these provinces lie on the efficiency frontier within the selected comparison set. Among them, Phuket recorded the highest super-efficiency score of 1.2499, followed by Samut Sakhon at 1.1107 and Rayong at 1.0295. These provinces can therefore be interpreted as the strongest benchmark cases for comparative sustainability performance.

Second, several provinces showed strong but not frontier-level performance. Samut Prakan, Khon Kaen, Pathum Thani, Kanchanaburi, Songkhla, Ayutthaya, and Chachoengsao recorded overall CCR efficiency scores above 0.9700, suggesting that they are relatively competitive within the selected DMU set. However, their super-efficiency scores varied, indicating that high overall CCR efficiency does not always translate into stronger frontier-based ranking. These provinces may serve as supporting benchmark cases or learning examples for improvement-oriented policy comparison.

Third, the lower-ranked provinces indicate where further investigation may be needed. Nakhon Ratchasima recorded the lowest overall CCR efficiency score of 0.8825 and the lowest super-efficiency score of 0.9206, followed by Chonburi and Chiang Mai with weaker comparative performance. These results do not imply that these provinces are economically unimportant. Rather, they suggest that they were less efficient in transforming development-related inputs and intermediate operational factors into final economic and environmental outcomes relative to the selected peer group. From a policy perspective,

these provinces may require closer examination of resource use, operational intensity, industrial structure, and environmental performance management.

Table 6. Core CCR-based efficiency results for the selected provinces.

Rank	DMU	Province	Overall CCR Efficiency	CCR Super-Efficiency
1	8	Phuket	1.0000	1.2499
2	15	Samut Sakhon	1.0000	1.1107
3	9	Samut Prakan	0.9855	1.0831
4	13	Khon Kaen	0.9753	1.0576
5	3	Rayong	1.0000	1.0295
6	16	Saraburi	0.9549	1.0292
7	12	Pathum Thani	0.9885	1.0062
8	14	Ratchaburi	0.9473	0.9859
9	11	Kanchanaburi	0.9824	0.9835
10	10	Songkhla	0.9711	0.9827
11	4	Ayutthaya	0.9718	0.9770
12	6	Chiang Mai	0.9402	0.9753
13	1	Bangkok	0.9532	0.9696
14	7	Chachoengsao	0.9888	0.9667
15	2	Chonburi	0.9176	0.9336
16	5	Nakhon Ratchasima	0.8825	0.9206

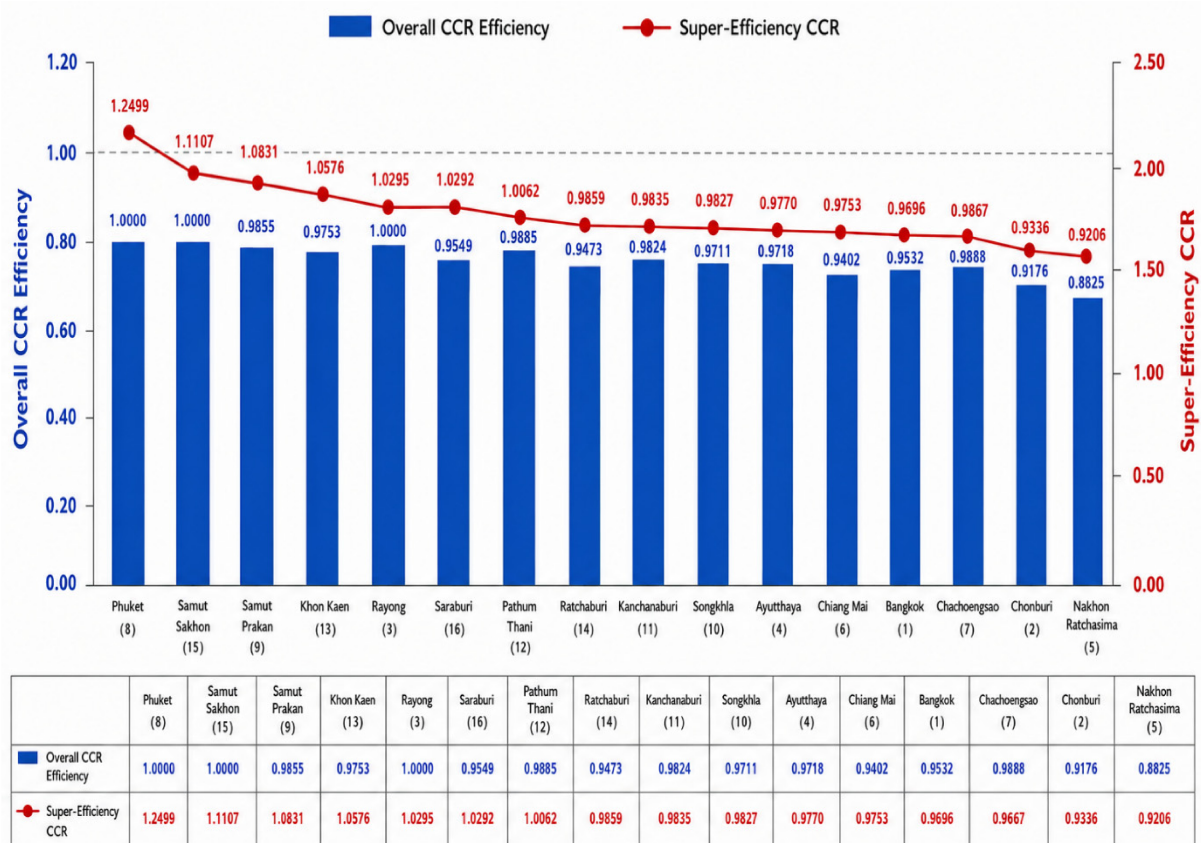


Figure 3. Overall CCR efficiency and super-efficiency rankings of the selected provinces.

Overall, Table 6 demonstrates that the AWVAA-based screening stage and the CCR-based DEA evaluation stage provide complementary information. AWVAA identifies provinces that are suitable and representative for benchmarking, while DEA reveals the relative efficiency differences among those selected provinces. This distinction is important because a province may be prominent in the screening stage but not necessarily emerge as the strongest efficiency benchmark. The results therefore support the use of the proposed AWVAA-CCR framework as a two-part decision-support process for identifying benchmark provinces, competitive performers, and priority improvement cases.

Figure 3 presents the CCR-based benchmarking results by jointly reporting overall efficiency and super-efficiency scores for the selected provinces. The bar chart presents the relative overall efficiency of each selected province, while the super-efficiency line provides additional discrimination among provinces located on or near the efficiency frontier. By ordering provinces according to super-efficiency performance, the figure transforms DEA outputs into an interpretable benchmarking structure that supports comparative assessment and decision-making.

5.3. Interpretation of Overall Efficiency and Super-Efficiency Results

Table 6 provides the main comparative benchmarking results for the 16 representative provinces selected through the AWVAA-based screening procedure. The results show that the selected provinces do not perform uniformly under the CCR-based two-stage DEA evaluation. Overall CCR efficiency scores ranged from 0.8825 to 1.0000, indicating clear differences among representative provinces in how effectively initial development conditions were converted into intermediate operational factors and final economic and environmental outcomes. The CCR super-efficiency scores ranged from 0.9206 to 1.2499, providing further discrimination among stronger-performing provinces.

The leading benchmark province was Phuket, with an overall CCR efficiency score of 1.0000 and the highest super-efficiency score of 1.2499. This means Phuket fared well compared to the chosen peer group and can be considered a benchmark case for efficient conversion of provincial development conditions into economic and environmental results. Samut Sakhon also crossed the efficiency frontier, with an overall CCR efficiency score of 1.0000 and a super-efficiency score of 1.1107, suggesting high benchmarking potential, especially in an industrial province environment. Rayong similarly recorded an overall CCR efficiency score of 1.0000, but its lesser super-efficiency score than Phuket and Samut Sakhon reflects a more moderate position among the frontier provinces.

Some provinces achieved high levels of overall efficiency but not quite at the frontier. For example, the overall ratings of CCR efficiency of Samut Prakan, Pathum Thani, Khon Kaen, Kanchanaburi, Songkhla and Ayutthaya were higher than 0.9700. These provinces can be regarded competitive performers in the chosen representative group, although there is still opportunity for improvement with respect to the strongest benchmark provinces. These results show that good provincial performance may be driven not only by major economic hubs but also by provinces efficiently turning available development resources into outputs.

Nakhon Ratchasima had the lowest overall CCR efficiency score of 0.8825 and the lowest super-efficiency score of 0.9206, at the bottom of the ranking. Chonburi and Chiang Mai also scored less well across the board when benchmarked against the leading provinces. These results do not suggest that these provinces are inconsequential in economic or geographical terms. Instead, the data imply that these provinces are less effective in converting their input and intermediate conditions into final economic and environmental outcomes within the chosen DEA comparison set. From a policy standpoint, these provinces may need further analysis to determine if the inefficiency is related to operational intensity,

environmental load, resource consumption, or the trade-off between economic production and air quality.

In general, Table 6 shows the benefit of using DEA following AWVAA-based screening. AWVAA determines the representative and analytically relevant provinces for benchmarking, but DEA based on CCR indicates the relative efficiency of the provinces. Hence, the results suggest a differentiated interpretation, with high-performing provinces serving as benchmarking references, mid-ranked provinces providing comparative learning instances, and lower-ranked provinces selected for further research and targeted performance improvement.

5.4. Relationship Between Screening Strength and Efficiency Performance

Overall CCR efficiency and super-efficiency are valuable metrics of provincial performance. However, their interpretation is more relevant when examined in conjunction with the AWVAA-based screening results. Within the proposed data-driven informatics system, AWVAA functions as the screening mechanism for selecting representative units, while the CCR-based two-stage DEA model executes the formal efficiency evaluation. Examining these components together helps clarify whether provinces identified as excellent candidates in the screening step also have strong relative performance in the efficiency stage.

Figure 4 shows the relationship between overall CCR efficiency and super-efficiency, with the size of the bubble representing the AWVAA score of each province. The picture summarizes three characteristics of the proposed framework: screening strength, relative efficiency, and frontier-based ranking discrimination. The provinces in the upper-right corner show reasonably good performance on overall CCR efficiency and super-efficiency, indicating stronger benchmarking potential among the chosen DMUs. On the contrary, provinces occupying lower-left positions exhibit lower relative efficiency or reduced discrimination in super-efficiency rankings. Table 7 is crucial because it translates these comparative tendencies into policy direction.

Table 7. Illustrative interpretation of provincial performance under the integrated AWVAA–CCR framework.

Province	Performance Pattern	Interpretation	Policy Implication
Bangkok	Strong screening but moderate DEA ranking	Very high AWVAA score indicates strong screening-stage prominence, but efficiency performance is more moderate relative to frontier provinces	Important policy reference province but not the strongest DEA benchmark
Phuket	Strong DEA benchmark with modest AWVAA screening score	Modest screening score, but excellent overall CCR efficiency and super-efficiency performance	Benchmark for high relative sustainability efficiency, especially in tourism-oriented contexts
Samut Prakan	Strong DEA performer with modest screening score	Retained through representative-unit logic and performs strongly in the DEA stage	Benchmark for industrial sustainability and downstream provincial benchmarking

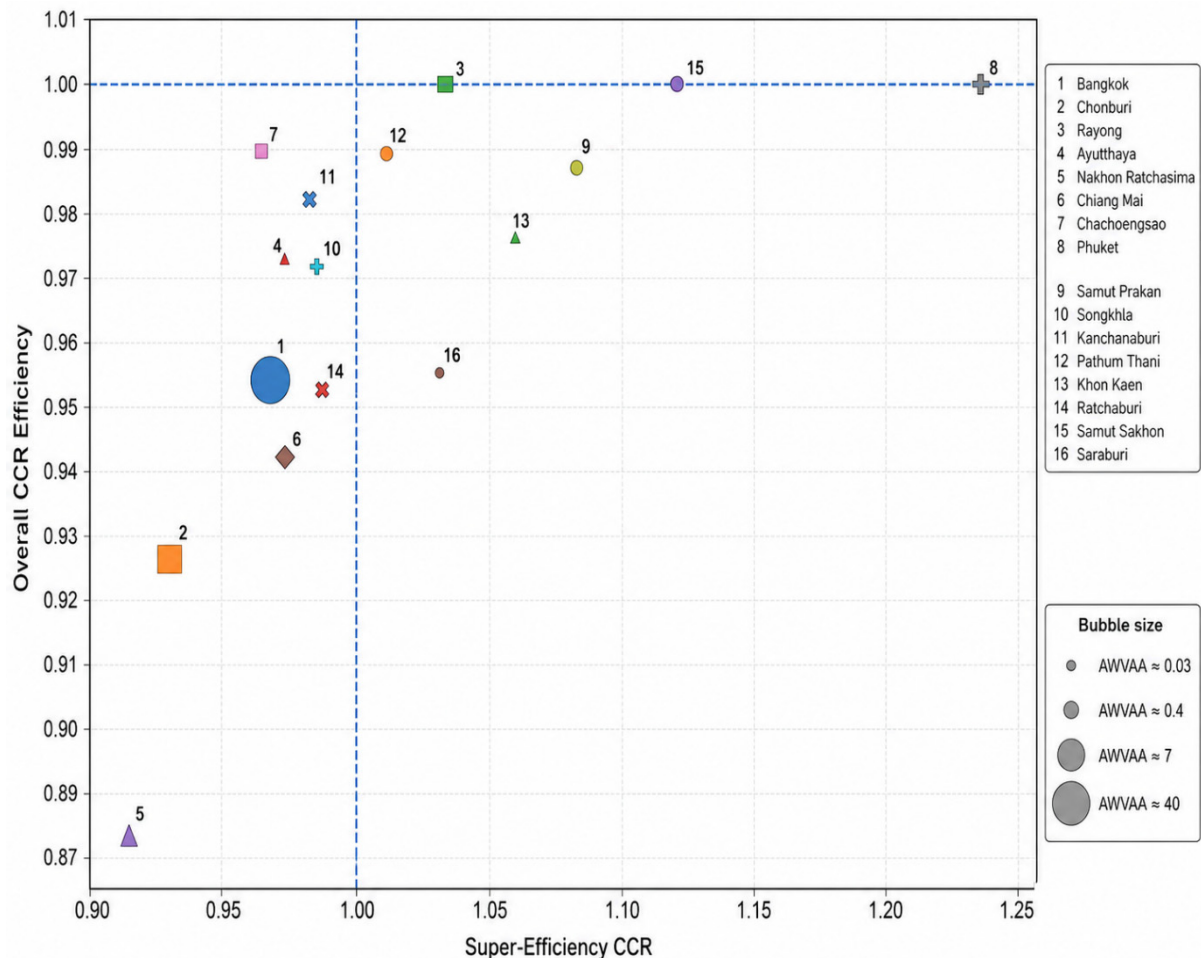


Figure 4. Relationship between overall CCR efficiency and super-efficiency of the selected provinces, with bubble size representing AWVAA screening scores.

The visualization of AWVAA scores as different bubble sizes introduces an additional layer of interpretation. Provinces with larger bubbles were considered good candidates during the screening stage, whereas provinces with smaller bubbles were retained due to the broader logic of representative unit selection and regional balance. Thus, Figure 4 shows whether good screening results always align with strong DEA-based efficiency performance. The given results are not in exact linear correspondence. Provinces with high AWVAA scores do not always rank high in overall or super-efficiency rankings, while some provinces with relatively low AWVAA scores rank well in DEA rankings. This shows that the screening stage and the efficiency stage capture related but different aspects of province performance.

This difference is key to appreciating what the framework brings to regional sustainability planning and resource optimization. AWVAA is not a substitute for a DEA review but instead provides a structured preselection technique to enhance the transparency and representativeness of the DMU set. Then, a CCR-based two-stage DEA model provides a comparative efficiency assessment inside the specified set. The interaction between the two elements of the framework is shown in Figure 4. The AWVAA stage produces provinces that enter the formal evaluation, and the DEA stage determines the relative performance of those provinces.

From a benchmarking point of view, the provinces in the upper-right region of Figure 4 can be regarded as benchmarking reference provinces since they have relatively high overall efficiency and stronger super-efficiency discrimination. Provinces with large AWVAA bubbles but weak efficiency positions may nevertheless be valuable because of their strong

screening-stage relevance but reduced relative efficiency in the formal evaluation stage. On the other hand, provinces with a tiny bubble but a strong DEA position illustrate that relative efficiency and representative selection are not the same notions. This supports the usefulness of the suggested framework as a combined selection-and-evaluation procedure rather than as a single ranking exercise.

Table 7 provides an interpretive synthesis of the benchmarking trends observed in Figure 4. The chosen instances illustrate that the performance of the provinces should be assessed by taking into account both the efficiency results from DEA and the screening importance from AWVAA. This difference suggests that the selection of representative units and efficiency benchmarking reflect complementary aspects of provincial sustainability performance.

5.5. Policy Interpretation and Benchmarking Implications

The last aspect of the proposed informatics architecture is data-driven interpretation and decision support. The combined outcomes of AWVAA screening and CCR-based DEA in the revised results structure provide a basis for understanding not only which provinces are strong performers in the formal evaluation stage but how those provinces entered the benchmarking process via representative unit selection.

From a policy perspective, the provinces in the stronger efficiency zone of Figure 4 can be regarded as benchmarking provinces in the selected DMU set. These provinces have relatively high overall CCR efficiency and stronger super-efficiency performance and can therefore serve as excellent reference points for sustainable provincial development. At the same time, the figure also demonstrates that provinces with high AWVAA scores may not necessarily receive the strongest DEA-based rankings. This divergence matters because it suggests that the screening stage and the efficiency stage tap into different but complimentary characteristics of provincial performance.

Provinces with high AWVAA scores and weaker relative DEA performance may remain policy important, as they are good candidates based on data completeness, regional representation, and screening-stage importance, despite not emerging as the strongest efficiency standards. On the other hand, provinces with relatively low AWVAA scores but with high CCR efficiency and super-efficiency scores show that good comparative performance can be observed even among those provinces that did not play an important role in the screening process. This makes the system particularly effective for searching for neglected benchmark situations.

In practice, the framework allows for diverse policy interpretation. Benchmark provinces with strong performance in DEA might be used as reference models for efficiency-oriented planning, while provinces with strong performance in AWVAA but relatively weak performance in DEA could be looked into more closely to understand why their prominence in the screening stage does not fully translate into relative efficiency performance. This distinction can help policymakers decide whether provincial improvement should be on the efficiency of execution, on environmental outcomes, or on regional development priorities.

Table 8 interprets the observed benchmarking patterns in a policy-oriented way by grouping provinces on the basis of their efficiency profile and possible improvement needs. The methodology enables more targeted benchmarking by differentiating screening-stage relevance from evaluation-stage performance instead of assuming that all selected provinces need the same answer. This suggests that the proposed strategy provides a more robust foundation for policy prioritization compared to using a single ranking mechanism.

Table 8. Benchmarking summary and policy directions for the selected provinces.

Performance Group	Province	Performance Profile	Main Implication	Suggested Policy Direction
DEA benchmark provinces	Phuket	Strong overall CCR efficiency and highest CCR super-efficiency, despite a modest AWVAA screening score	Demonstrates strong relative efficiency within the selected DMU set	Use as a benchmark for sustainability-oriented tourism development and efficient provincial management
DEA benchmark provinces	Samut Sakhon	Strong DEA performance with high super-efficiency, despite a relatively small AWVAA screening score	Illustrates that strong benchmarking value may emerge beyond the most prominent screening-stage provinces	Use as a benchmark for industrial sustainability and operational efficiency improvement
DEA benchmark provinces	Samut Prakan	Strong DEA performance with high super-efficiency and moderate screening-stage prominence	Combines representative selection with strong comparative efficiency	Use as a benchmark for coordinated industrial-environmental development
Screening-prominent but moderate DEA performers	Bangkok	Highest AWVAA screening score but more moderate super-efficiency position than leading DEA benchmark provinces	Strong relevance in the screening stage does not automatically imply strongest comparative efficiency	Maintain role as a major reference province while identifying gaps between development prominence and relative efficiency
Screening-prominent but moderate DEA performers	Chonburi	Very strong AWVAA score but weaker DEA ranking relative to leading benchmark provinces	Strong provincial prominence at the screening stage is not fully matched by DEA performance	Improve efficiency-oriented management and environmental performance relative to development scale
Screening-prominent and competitive performers	Rayong	Strong AWVAA score and high DEA ranking	Demonstrates consistency between screening-stage strength and DEA-based performance	Use as a benchmark for integrated industrial and sustainability policy planning
Mid-ranked benchmark-support provinces	Pathum Thani	Moderate AWVAA score and strong overall CCR performance	Supports the view that provinces with modest screening prominence may still perform strongly in DEA evaluation	Use as a supporting benchmark for balanced provincial planning
Mid-ranked benchmark-support provinces	Khon Kaen	Low AWVAA score but strong super-efficiency ranking	Reveals the value of the framework in identifying less prominent but highly efficient provinces	Examine as a benchmark for hidden or underrecognized provincial efficiency

Table 8. *Cont.*

Performance Group	Province	Performance Profile	Main Implication	Suggested Policy Direction
Mid-ranked benchmark-support provinces	Saraburi	Low AWVAA score but relatively strong super-efficiency performance	Shows that smaller screening-stage presence does not prevent competitive DEA outcomes	Use as a comparative case for improvement-oriented benchmarking
Transitional provinces	Ayutthaya	Moderate DEA performance with stronger policy relevance than efficiency leadership	Competitive but not frontier-leading	Strengthen efficiency management while preserving balanced development performance
Transitional provinces	Songkhla	Moderate overall CCR efficiency and lower super-efficiency performance	Retained as a representative province but not a leading benchmark	Improve regional management and sustainability-oriented performance efficiency
Transitional provinces	Kanchanaburi	Moderate DEA position with limited screening prominence	Useful as a representative case but not a frontier benchmark	Improve operational efficiency and policy implementation capacity
Priority-improvement provinces	Chiang Mai	Lower DEA performance despite selection as a representative province	Indicates need for improvement in relative sustainability efficiency	Focus on strengthening comparative efficiency in development and environmental management
Priority-improvement provinces	Chachoengsao	Lower super-efficiency despite acceptable overall CCR efficiency performance	Suggests weaker relative discrimination under frontier analysis	Improve performance consistency and benchmarking competitiveness
Priority-improvement provinces	Ratchaburi	Lower DEA position and limited screening-stage prominence	Weak benchmarking position under both screening and evaluation logic	Prioritize efficiency improvement and targeted provincial development support
Priority-improvement provinces	Nakhon Ratchasima	Lowest DEA performance among the selected provinces	Represents the clearest case for policy attention under the integrated framework	Prioritize structural reform, investment efficiency, and sustainability-oriented performance improvement

5.6. Discussion in Relation to the Proposed Framework

The results validate the analytical logic of the proposed data-driven informatics framework from two major aspects. The first screening stage based on AWVAA was able to choose a representative and geographically balanced subset of provinces out of the larger dataset at the national level. This demonstrates that the framework enhances the transparency of province selection by substituting an ad hoc preparation with a structured and reproducible screening procedure. Secondly, the CCR-based DEA evaluation indicated that there were significant disparities in the overall efficiency and super-efficiency ranking of the selected provinces. This suggests that the screening process of the representative-unit maintains sufficient variability for comparative benchmarking and policy interpretation.

The results also show the consistency of the proposed framework as a decision-support sequence. The AWVAA phase reduced a huge and varied provincial dataset to a manageable and analytically appropriate set of representative DMUs. The DEA phase explained the relative performance of those provinces under the shared efficiency frontier. The framework combines screening stage information with efficiency stage evaluation for a more holistic interpretation than either component alone.

A main take-away from Figure 4 is that screening prominence and DEA-based efficiency are linked but not equivalent. Some provinces with extremely good AWVAA scores were not among the strongest DEA benchmark provinces, whereas a number of provinces with quite modest screening scores performed well on overall CCR efficiency and super-efficiency. This distinction is essential because it demonstrates that the screening step and the assessment stage capture different characteristics of provincial performance. AWVAA enhances representativeness and transparency in the selection of DMUs, while CCR efficiency and super-efficiency help clarify the comparative efficiency among the selected set.

In terms of informatics, the framework enables disparate provincial data to be systematized into a reproducible analytical workflow that includes data completeness screening, representative unit selection, DEA-based benchmarking, and policy interpretation. This framework does more than just generate rankings. It presents regional sustainability assessment as a transparent, evidence-based process of data organization, transformation, and evaluation.

Overall, this study verifies the suggested AWVAA-CCR framework as a combined mechanism for selecting representative units and evaluating comparative efficiency. Its key benefit is to combine a transparent screening step with a formal benchmarking stage in an interpretable, reproducible, and policy-relevant manner. This makes the approach highly relevant for provincial benchmarking, sustainability monitoring, and evidence-based regional planning.

5.7. Limitations of the Empirical Analysis

Several restrictions should be noted in interpreting the results. First, the study is dependent on the availability of comprehensive province data, which limited the number of qualifying provinces to join the formal efficiency stage. The final group of representative provinces is therefore a function of data availability and analytical choice rather than a reflection of the entire national population of provinces. Second, while the selected variables capture the essential features of economic and environmental performance, they do not exhaust all viable measures of sustainability. The system can be further enriched for future applications by incorporating social, health, climatic, and land-use aspects. Third, the updated empirical analysis is based on the CCR-based two-stage DEA model for methodological clarity and consistency with the altered study design. This targeted approach enhances defensibility and interpretability, but it also implies that alternative model structures are beyond the purview of the present investigation. Future work can extend the concept to longitudinal evaluation, other characteristics of sustainability, or more advanced predictive decision support settings.

6. Conclusions, Limitations, and Future Studies

This study presents a data-driven informatics framework to assess provincial sustainability performance in Thailand by combining a CCR-based two-stage data envelopment analysis framework with an additive weighting-based variant assessment algorithm (AWVAA). The suggested technique was intended to answer a practical problem of regional assessment: how to transition from a vast and varied provincial dataset to a transparent,

representative, and policy-relevant evaluation of economic production and environmental sustainability. This study contributes a cohesive analytical workflow for provincial benchmarking and decision support by integrating representative province screening and comparative efficiency evaluation.

The initial contribution of the study is the AWVAA-based screening of representative provinces. This stage is formalized in the framework with data completeness screening, global SAW evaluation, local SAW evaluation, and rigorous global SAW re-evaluation, instead of treating the DMU selection as informal pre-processing. This technique enhances the openness and repeatability of province selection by guaranteeing that the final representative set reflects not only the national screening performance but also the regional balance. Thus, AWVAA serves as a structured preselection process in the larger informatics scheme.

The second contribution of the study is the efficiency evaluation and super-efficiency benchmarking of the selected provinces based on CCR. The results demonstrate significant variances in overall CCR efficiency and super-efficiency performance among provinces, demonstrating that the selected provinces are not a uniform benchmark group. Rather, certain provinces emerge as stronger DEA-based benchmark examples, while others are more essential as representative units discovered through the screening stage. This distinction is useful because it implies that prominence in the screening stage and efficiency in the performance stage are related but not identical characteristics of provincial assessment.

The findings have one crucial implication: the two components of the framework have complementary functions. The AWVAA stage increases representativeness and transparency in the selection of provinces, while CCR efficiency and super-efficiency clarify the relative performance among the selected set. Figure 4 captures this link, showing that provinces with the highest AWVAA scores are not necessarily those with the highest DEA-based rankings and that some provinces with modest screening scores are good comparative benchmarks. The framework is emphasized more as an integrated selection-and-evaluation approach than as a single ranking exercise.

The key contribution of this study from an informatics perspective is its capacity to structure diverse provincial data into a replicable workflow for analysis, combining data screening, selection of representative units, benchmarking using DEA, comparative ranking, and policy interpretation. The methodology not only produces scores but also conceptualizes regional sustainability assessment as an open and evidence-based process of data organization, transformation, and evaluation. This makes it valuable for academic study, sustainability monitoring, provincial benchmarking, and evidence-based planning.

This study also provides practical consequences for policymakers. The provinces that have strong CCR efficiency and super-efficiency performance may be benchmark provinces for efficiency-oriented sustainability planning. The provinces that are strong in the AWVAA screening stage but weak in DEA performance may need to be examined further to understand why their prominence in development is not fully translated into relative efficiency. This distinction allows for a more nuanced prioritizing of policies and ensures that not all selected provinces play the same role in benchmarking.

There are a few constraints to keep in mind. First, this empirical study relies on the availability of comprehensive provincial data, which limited the number of provinces suitable for formal examination. Second, the AWVAA screening approach is sensitive to the specified criteria, weighting logic, and normalizing structure, which implies that alternate screening designs may lead to somewhat different representative sets. Third, the CCR efficiency and super-efficiency scores should be viewed as relative efficiency indicators within the group selected and not as absolute measurements of sustainable

performance. Finally, the chosen indicators reflect essential aspects of economic and environmental performance but do not cover all dimensions of sustainability. Future research can expand the framework to include social, health, governance, climatic, and land-use aspects.

Future studies could extend the concept in numerous ways. A sensitivity study on the screening assumptions for AWVAA could bolster the robustness of representative unit selection. Dynamic or longitudinal DEA models can be used to study performance changes over time. Moreover, the existing framework can be extended with predictive analytics or machine learning techniques to provide better decision support in increasingly complicated regional policy situations.

Overall, this study shows that the combination of AWVAA-based representative province screening and CCR-based efficiency and super-efficiency evaluation provides a feasible and informative framework for evaluating provincial sustainability performance in Thailand. The suggested data-driven informatics architecture provides a systematic basis for provincial benchmarking, sustainable governance, and evidence-based regional planning.

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