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Urban–Regional Disparities in Economic Prosperity and Distributional Outcomes: A TOPSIS-Based Provincial Ranking of Thailand

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Abstract

Economic development is multidimensional, yet provincial comparisons in Thailand often rely on individual indicators or broad sustainability indices. This study constructs separate TOPSIS rankings of economic prosperity and distributional outcomes for all 77 Thai provinces. Six prosperity indicators capture economic output, human capital, spatial agglomeration, labor market outcomes, and structural transformation, while four distributional indicators capture income inequality, economic vulnerability, informal employment, and household dependency. The analysis uses 2024 provincial accounts and Labor Force Survey microdata, with comparisons for 2022–2024. Prosperity is concentrated in Bangkok, the surrounding metropolitan region, and the Eastern Seaboard, while Phuket represents a distinct tourism-led pathway. Favorable distributional outcomes are concentrated within the metropolitan–industrial corridor, whereas disadvantage is more prevalent in the North and Northeast. The rankings are associated but conceptually distinct, and the prosperity ranking differs meaningfully from one based solely on GPP per capita. The prosperity ranking is highly stable over time, while the distributional ranking exhibits substantial stability after harmonizing income coverage. Both rankings are robust to alternative normalization procedures, weighting schemes, and aggregation methods. Spatial statistics confirm clustering. The findings demonstrate the value of separating economic prosperity from distributional disadvantage when benchmarking provincial development and assessing urban–regional disparities.

Keywords: urban–regional disparities; economic prosperity; distributional outcomes; economic vulnerability; provincial development; TOPSIS; provincial ranking; Thailand



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1. Introduction

Thailand exhibits substantial and persistent spatial disparities in economic development. The Bangkok Metropolitan Region (BMR), comprising Bangkok and the five surrounding provinces of Nonthaburi, Pathum Thani, Samut Prakan, Samut Sakhon, and Nakhon Pathom, forms the country's dominant economic core, while many provinces outside the principal metropolitan and industrial centers continue to lag behind. Between 2015 and 2024, the Bangkok Metropolitan Region consistently accounted for approximately 46–48 percent of national GDP at current prices, while its share of the national population increased from approximately 23 to 25 percent (Authors' calculations based on National Economic and Social Development Council (NESDC) provincial accounts). Economic activity has also become concentrated along the Eastern Seaboard, where industrial development,

infrastructure investment, and access to major markets have created a second major axis of provincial prosperity. These patterns illustrate the continuing influence of urban primacy, agglomeration, and uneven regional development on Thailand's economic geography.

Urban and regional economic theories explain how agglomeration economies, labor market pooling, knowledge spillovers, market access, and scale effects generate cumulative advantages for locations that attract firms, workers, and investment [1]. These processes can raise productivity and income in metropolitan centers and industrial clusters while reinforcing disparities between core and peripheral regions. However, the concentration of economic activity does not reveal whether its benefits are broadly shared within each province. A province may generate substantial output and income while retaining high inequality or a large economically vulnerable population. Conversely, a less prosperous province may achieve comparatively favorable distributional outcomes.

Economic prosperity and distributional outcomes are therefore related but distinct dimensions of provincial development. Economic prosperity reflects economic performance and the conditions that support it, including income, human capital, urbanization, and labor market performance. Distributional outcomes capture the degree of income inequality and economic vulnerability within a province and therefore indicate how broadly the benefits of development are shared across its population. Combining these dimensions into a single score could conceal meaningful differences among provinces. The present study consequently evaluates them separately.

Composite indicators provide a practical means of integrating several dimensions of regional performance and revealing spatial patterns that may not be evident from individual indicators. Thailand possesses extensive provincial-level socioeconomic information. The National Economic and Social Development Council regularly publishes Gross Provincial Product and related provincial accounts, while the National Statistical Office and other government agencies provide information on household income, education, employment, urbanization, and living conditions. Nevertheless, systematic measures that integrate these indicators into a common framework for comparing provincial economic development remain limited. Provincial comparisons continue to rely heavily on individual measures such as GPP per capita, which capture aggregate production but provide only a partial representation of economic well-being.

Thailand has also developed broader systems for monitoring multidimensional development. The Provincial SDG Index produced by SDG Move [2] evaluates all 77 provinces across the 17 Sustainable Development Goals and the dimensions of People, Prosperity, Planet, Peace, and Partnership. The index is particularly useful when the objective is to evaluate the sustainability of provincial development across economic, social, environmental, and institutional dimensions.

Sustainable development, however, is not always the principal outcome of interest. For questions concerning regional economic well-being, an overall SDG score may provide a different interpretation of provincial performance because favorable environmental, social, or institutional outcomes can compensate for weaker economic conditions. Several Northeastern provinces, for example, perform relatively well in the overall Provincial SDG Index partly because of strong results in environmental and institutional dimensions, even though the Northeast continues to face substantial disadvantages in income, economic opportunity, and other measures of material well-being [2]. These provinces may therefore rank favorably in terms of sustainability without necessarily being regarded as among Thailand's more economically developed provinces.

An economically focused framework is useful when the analytical objective is to compare provincial economic capacity and the material well-being of residents. This does not imply that economic outcomes are more important than environmental, social, or institu-

tional conditions. Rather, different indices are appropriate for different research and policy questions. The Provincial SDG Index evaluates the broader sustainability of provincial development, whereas the rankings constructed in this study identify where economic prosperity is concentrated and whether its benefits are broadly shared. Restricting the analysis to economic outcomes reduces compensation from conceptually distinct dimensions and provides rankings with a clearer interpretation for regional economic policy.

To address this gap, the study constructs separate rankings of economic prosperity and distributional outcomes for all 77 provinces using the Technique for Order Preference by Similarity to the Ideal Solution, or TOPSIS. TOPSIS is selected because it evaluates every province against the same positive and negative ideal benchmarks, providing a transparent and readily interpretable basis for comparing performance across multiple indicators. This common-reference approach is well suited to the objective of the study, which is to rank provinces according to shared standards of economic prosperity and favorable distributional outcomes rather than to identify statistically derived components or estimate province-specific efficiency frontiers. A fuller comparison of TOPSIS with alternative approaches, including Principal Component Analysis and Data Envelopment Analysis, is provided in Section 2.4.

The economic prosperity ranking incorporates measures of economic performance, household income, human capital, urbanization, labor market conditions, and structural transformation. The distributional outcomes ranking incorporates measures of income inequality, economic vulnerability, informal employment, and demographic dependency. Evaluating these dimensions separately makes it possible to determine whether provinces with stronger economic foundations also achieve outcomes that are broadly favorable across their populations.

This study makes four main contributions. First, it develops a multidimensional framework for ranking the economic development of all 77 Thai provinces, moving beyond comparisons based solely on GPP per capita or other individual indicators. Second, it separates economic prosperity from distributional outcomes, allowing the scale of provincial economic development to be distinguished from the extent to which its benefits are broadly shared. Third, the indicators underlying each ranking are selected through a systematic evaluation of candidate measures grounded in the development and regional economics literature, retaining indicators that capture a conceptually distinct dimension of development and excluding those found to substantially duplicate existing measures; this yields a theoretically grounded and empirically parsimonious set of six economic prosperity indicators and four distributional outcome indicators, rather than a fixed or arbitrarily determined list. Fourth, it reveals spatial patterns of provincial advantage and disadvantage that may be overlooked by single-indicator measures or broad composite indices designed to assess different dimensions of development.

The results reveal a pronounced concentration of economic prosperity in Bangkok, the surrounding metropolitan region, and the Eastern Seaboard, while less favorable outcomes remain more common in the North and Northeast. Phuket also illustrates a distinct tourism-led pathway outside the principal metropolitan–industrial core. The prosperity ranking is highly stable over time, while the distributional ranking remains substantially stable after harmonizing income coverage. The results demonstrate the value of evaluating economic prosperity and distributional outcomes separately.

2. Literature Review

2.1. Composite Rankings and the Measurement of Regional Development

Composite ranking systems have become widely used tools for evaluating the relative performance of cities, provinces, and regions, reflecting the recognition that development

is multidimensional and cannot be adequately represented by a single indicator such as income or economic output. This perspective is rooted in the capability approach, which defines development in terms of people's substantive opportunities and achievements rather than material resources alone [3], and has been operationalized through multidimensional frameworks such as the Human Development Index [4].

Subnational ranking systems apply this multidimensional perspective to different purposes. Broad development indices, such as the China Integrated City Index, assess cities across economic, social, and environmental dimensions and have consistently found economic advantage concentrated in a small set of leading cities [5]. Competitiveness and business-environment indices, including Vietnam's Provincial Competitiveness Index and Indonesia's Provincial Competitiveness Analysis, emphasize governance quality and institutional conditions rather than economic outcomes directly [6,7]. Labor-market and urban-performance indices, such as India's Regional Competitiveness Index and the Milken Institute's Best-Performing Cities Index, link competitiveness to economic growth and technological dynamism [8,9].

These systems differ not merely in their methods but in what they define as successful development: a competitiveness index prioritizes the conditions supporting business activity, while a sustainability index incorporates a wider set of social and environmental objectives. A composite index therefore embeds normative choices about which outcomes matter and whether strengths in one dimension should compensate for weaknesses in another; its usefulness depends on how closely its design matches the research question at hand.

2.2. Spatial Inequality and Uneven Regional Development

Urban and regional economic theories emphasize that economic activity tends to concentrate geographically because firms and workers benefit from agglomeration economies, market access, knowledge spillovers, and increasing returns to scale [1], raising productivity in metropolitan centers and industrial clusters while widening disparities with peripheral regions. Broader theories of uneven geographical development explain why these differences become structurally persistent: Smith [10] argues that capital accumulation continually produces spatial differentiation by directing investment toward advantageous locations while withdrawing it from others, so that regional prosperity and disadvantage emerge as interconnected outcomes of the same development process rather than independent differences in local endowments.

Peripheralization, spatial justice, and the capability approach together explain why aggregate prosperity and broadly shared well-being may diverge. The peripheralization literature conceptualizes peripheral regions as places produced through processes of economic, social, and political marginalization rather than simply as locations distant from urban centers, so that disadvantage can persist even when national performance improves [11]. Spatial justice adds a normative dimension by treating the geographic distribution of resources, opportunities, and well-being as a legitimate concern of public policy [12], while the capability approach reinforces that development should be assessed by the opportunities it generates for people, not only the resources produced in a place [3].

International evidence supports these arguments across multiple scales and settings. Spatial disparities in income and opportunity remain persistent in both developed and developing economies because of differences in agglomeration, market access, infrastructure, and factor mobility [13], with divergence between European metropolitan centers and lagging regions linked to both weaker performance and rising political discontent [14,15]. Comparable patterns appear at other scales and in other settings: trade-driven local labor market shocks in the United States [16] and geographically concentrated capital defi-

ciencies constraining household consumption growth in rural China [17] both show that national averages conceal durable place-based differences that economic performance alone cannot describe.

2.3. Spatial Disparities and Provincial Measurement in Thailand

Thailand reflects many of the patterns identified in the international literature, with economic activity long concentrated in Bangkok and its surrounding provinces and provincial outcomes exhibiting substantial spatial dependence.

Using provincial data from 1995 to 2017, Tipayalai and Mendez [18] find significant spatial dependence in per capita income and identify distinct convergence clubs among Thai provinces rather than convergence toward a single national equilibrium. Their findings suggest that uniform nationwide policies may be poorly suited to geographically differentiated development constraints.

Based on evidence from local governments, Kamnuansilpa et al. [19] argue that economic development policy has historically favored top-down, place-based interventions concentrated in already-prosperous regions. Such policies may reinforce existing spatial advantages rather than offset them [20].

Puttanapong et al. [21] provide complementary evidence using satellite-derived nighttime-light data, finding that socioeconomic activity remains strongly clustered around Bangkok despite only gradual diminishment over time. They recommend developing polycentric growth poles as an alternative to continued dependence on the capital.

Together, these studies show that Thai regional inequality is spatially dependent, persistent, and reinforced by the concentration of investment and policy support. However, they do not provide a multidimensional province-level comparison that distinguishes economic prosperity from the distribution of its benefits.

The Provincial SDG Index represents the most comprehensive existing system for assessing development across all 77 Thai provinces. It evaluates provincial performance across the 17 Sustainable Development Goals and the broader dimensions of People, Prosperity, Planet, Peace, and Partnership. Its purpose is not limited to economic comparison. Rather, it is designed to identify sustainability challenges, assess provincial and regional risks, support stakeholder validation and prioritization, and inform science, research, innovation, and policy planning. The framework therefore incorporates a wide range of economic, social, environmental, institutional, and infrastructural indicators [2].

Several indicators in the Provincial SDG Index overlap with, or relate closely to, the economic and distributional dimensions examined in the present study. These include the Gini coefficient, informal employment, poverty incidence, household debt, unemployment, educational participation and achievement, and measures of infrastructure and market access. However, similar concepts are often operationalized differently. The Provincial SDG Index uses the growth rate of GPP per capita, whereas the present study uses its real level as an indicator of accumulated economic capacity. It evaluates education primarily through participation, completion, literacy, and learning outcomes, whereas the prosperity ranking measures educational attainment among the working-age population. The present framework also includes urban population share, employment density, average monthly income, and the non-agricultural share of GPP, which jointly capture agglomeration, labor-market performance, and structural transformation but are not combined as a distinct measure of provincial economic foundations within the SDG framework.

The two approaches also differ in their benchmarking logic. The Provincial SDG Index evaluates indicators against goal-specific thresholds and assigns status categories intended to identify areas of achievement, challenge, or critical concern. TOPSIS instead compares each province with positive and negative ideal values constructed from the

observed provincial data. Its scores therefore represent relative standing within the national comparison set rather than progress toward externally specified sustainability targets. This methodological distinction means that the two systems can generate different assessments even when they include related indicators.

These differences do not imply a weakness in either framework. They reflect distinct analytical purposes. The Provincial SDG Index is designed to evaluate the breadth of provincial sustainability challenges across the full SDG agenda, whereas the rankings developed in this study isolate economic prosperity and distributional outcomes for urban and regional economic analysis. Broad sustainability performance may therefore diverge from economic well-being because favorable environmental, institutional, or social outcomes can offset weaker economic conditions in an overall index. Several Northeastern provinces, for example, perform relatively well in the Provincial SDG Index partly because of stronger results in environmental and institutional dimensions, despite continuing disadvantages in income, economic opportunity, and material well-being. The present rankings complement rather than replace the Provincial SDG Index by providing a more focused assessment of where provincial economic capacity is concentrated and where economic disadvantage remains most pronounced.

2.4. TOPSIS in Urban and Regional Analysis

Constructing a composite ranking requires a method for combining indicators that differ in units, direction, and relative performance. Within urban and regional research, TOPSIS has been used to assess competitiveness, development, and quality of life. Ferrarini, Muzzioli, and De Baets [22] apply TOPSIS to rank 268 NUTS-2 (NUTS-2 (Nomenclature of Territorial Units for Statistics, level 2) refers to the European Union's standard classification of major socio-economic regions used for regional statistics and policy) regions in the European Union according to regional competitiveness, showing that the method can reproduce and refine established measures such as the EU Regional Competitiveness Index while accounting for relationships among indicators. At the intraurban level, Vakili-pour et al. [23] compare TOPSIS with VIKOR, Simple Additive Weighting, and ELECTRE in evaluating quality of life across urban spatial units, finding that TOPSIS produces broadly consistent rankings while remaining comparatively transparent to implement and interpret.

Beyond spatial applications, TOPSIS has been widely used in technology and vendor selection, performance evaluation, material choice, and strategic planning [24–36], demonstrating its flexibility in ranking alternatives across multiple conflicting criteria.

TOPSIS also offers specific methodological advantages relative to other MCDM approaches. Unlike pairwise-comparison methods such as the Analytic Hierarchy Process, TOPSIS does not require pairwise judgments between criteria, avoiding the inconsistency problems that can arise as the number of attributes grows [37]. It makes full use of the available attribute information, provides a cardinal rather than merely ordinal ranking of alternatives, and does not require the criteria preferences to be independent of one another [38,39].

The choice of TOPSIS can be understood through comparison with two alternative approaches to composite measurement [40]. PCA is a data-reduction technique that derives statistically determined weights from the covariance or correlation structure of the indicators, which can be difficult to interpret when indicators are only moderately correlated or when statistical variation does not correspond to substantive importance. DEA evaluates each unit relative to an efficiency frontier constructed from the sample, often allowing each unit its own most favorable weights—useful for efficiency analysis, but less appropriate when all units are meant to be compared against a common standard.

TOPSIS instead evaluates each alternative according to its distance from a common positive ideal solution and a common negative ideal solution, so that every province is assessed against the same reference points. This property corresponds closely to the objective of the present study, which is not to estimate latent statistical components, as in PCA, or province-specific efficiency, as in DEA, but to compare all 77 provinces against a shared benchmark of economic prosperity and a separate shared benchmark of favorable distributional outcomes.

The literature therefore establishes three foundations for the analysis: regional development is multidimensional but must be measured according to its analytical purpose; spatially concentrated prosperity does not necessarily produce broadly distributed gains; and TOPSIS offers a transparent, common-reference method well suited to comparing provinces across multiple indicators.

3. Materials and Methods

3.1. Conceptual Framework and Indicator Selection

The indicator framework addresses two analytically distinct questions: the strength of a province's economic foundations and the extent of distributional disadvantage experienced by its residents. Indicators were selected according to three principles: coverage of the major dimensions identified in the development and regional economics literature, avoidance of unnecessary duplication, and consistent measurability across all 77 provinces. The six economic prosperity indicators represent five dimensions of provincial development: economic output, human capital, spatial agglomeration, labor market performance, and structural transformation. The four distributional outcome indicators represent inequality, material vulnerability, labor market insecurity, and demographic pressure on household resources. The unequal number of indicators across the two rankings is therefore intentional. The resulting six-and-four structure provides broad conceptual coverage while remaining sufficiently parsimonious to preserve the interpretation of each ranking. Table 1 summarizes the conceptual dimension represented by each indicator and its data source; complete variable definitions and construction procedures are reported in Appendix A.

The economic prosperity ranking captures multiple dimensions of provincial economic development rather than relying exclusively on economic output. GPP per capita provides a summary measure of provincial production and the accumulated growth determinants emphasized by the augmented Solow framework, including physical capital and technology that cannot be observed consistently at the provincial level [41–43]. Educational attainment is included separately because human capital constitutes a distinct determinant of productivity and long-run growth [44,45].

Urban population share and employment density jointly capture spatial agglomeration. The former reflects population concentration in municipal areas, while the latter measures the intensity of employment within provincial space. Both are grounded in New Economic Geography, which emphasizes scale economies, market access, labor pooling, and knowledge spillovers [46]. Employment density also follows empirical work linking the spatial concentration of employment to productivity [1]. Because provincial boundaries are administrative rather than functional economic areas, employment density is partly sensitive to provincial land area and may favor geographically compact provinces; it is therefore interpreted as an imperfect proxy for agglomeration intensity. The relationship between urbanization and prosperity may run in both directions: agglomeration can raise productivity and incomes, but higher incomes and stronger labor demand can themselves attract population into municipal areas. Urban population share is retained as a prosperity indicator on the basis of the former, better-established channel, while this reverse path-

way is acknowledged as a limitation on causal interpretation of the composite ranking (Section 6).

Table 1. Criteria used in provincial rankings.

Dimension	Indicator	Variable Definition	Source
Economic Prosperity			
Economic output	GPP per capita	Real GPP per capita	NESDC
Human capital	Educational attainment	Share of the working-age population with secondary or tertiary education	LFS
Spatial agglomeration	Urban population share	Share of the working-age population residing in municipal areas	LFS
	Employment density	Employed persons per square kilometer	LFS and NESDC
Labor market outcomes	Average monthly income	Average real monthly income	LFS
Structural transformation	Non-agricultural GPP share	Non-agricultural share of gross provincial product	NESDC
Distributional Outcomes			
Inequality	Gini coefficient	Gini coefficient of income among working-age income earners	LFS
Material vulnerability	Economic vulnerability	Share of working-age income earners below twice the province-specific poverty line	LFS; NESDC
Labor market insecurity	Informal employment share	Share of working-age employed persons in informal employment	LFS
Demographic pressure	Household dependency ratio	Ratio of non-working household members to employed working-age household members	LFS

Average monthly income represents the labor market dimension of prosperity. Provinces with similar GPP per capita may differ in the extent to which economic activity translates into earnings for workers. Income therefore complements the output-based measure by capturing labor market performance more directly. Non-agricultural GPP share represents structural transformation, a central feature of development in which production shifts away from agriculture toward manufacturing and services [47,48]. It captures the composition rather than the level of provincial economic activity and therefore adds information that is not contained in GPP per capita or income alone.

Taken together, the six indicators cover economic output, human capital, agglomeration, labor market performance, and structural transformation. The framework does not capture every potentially relevant dimension of provincial development because comparable measures for several dimensions are not available at the provincial level in Thailand. The selected indicators therefore balance theoretical relevance, parsimony, and comparability across all 77 provinces.

The distributional outcome ranking focuses on how economic resources and vulnerabilities are distributed within provinces. It combines four indicators: the Gini coefficient, economic vulnerability, informal employment share, and the household dependency ratio. These indicators capture related but distinct forms of disadvantage that cannot be represented adequately by a single inequality or poverty measure.

The Gini coefficient captures inequality across the full distribution of reported income among income earners. It is included as the principal measure of within-province income inequality. The Palma ratio was also considered as an alternative measure of inequality but was excluded because it was highly correlated with the Gini coefficient ($r = 0.94$),

adding little distinct information while increasing the weight assigned to inequality [49]. Economic vulnerability is measured as the share of income earners with income below twice the province-specific poverty line [50,51]. Consistent with the vulnerability literature, this threshold captures individuals who are not officially poor but remain economically insecure [52–54].

Beyond income-based measures, informal employment share captures labor market insecurity that is not fully reflected in current earnings. Informal workers typically have more limited access to social insurance, employment protections, and stable earnings than formally employed workers. Informality has consequently been associated with greater vulnerability, poverty, and inequality across developing economies [55], including in Thailand specifically [56]. Its inclusion distinguishes provinces in which similar observed income distributions are supported by substantially different levels of employment security.

The household dependency ratio captures pressure on household resources by comparing the weighted number of non-working household members with the weighted number of employed working-age members. Higher values indicate that fewer earners support more dependents, a condition associated with greater economic vulnerability [57].

To assess potential duplication among the criteria, pairwise Pearson correlations were calculated separately for the economic prosperity and distributional outcome indicators.

Among the six prosperity indicators, the strongest relationships are between urban population share and employment density ($r = 0.69$), educational attainment and average monthly income ($r = 0.67$), GPP per capita and non-agricultural GPP share ($r = 0.66$), and GPP per capita and educational attainment ($r = 0.63$). The full results are reported in Appendix A Table A1. These correlations indicate that the indicators are related but not empirically interchangeable. Although TOPSIS does not require uncorrelated criteria [40], correlation may reinforce economic advantages that tend to occur together. The indicators are nevertheless retained because each represents a conceptually distinct dimension of provincial prosperity.

For the four distributional outcome indicators, pairwise correlations range from 0.48 to 0.72, with the strongest relationship between the Gini coefficient and economic vulnerability. The full results are reported in Appendix A Table A2. These values likewise suggest that the indicators capture related but distinct forms of disadvantage. Some reinforcement of shared disadvantage is possible, but all four are retained because they represent distinct monetary, labor market, and demographic dimensions.

3.2. Data Sources and Descriptive Statistics

The main analysis covers all 77 provinces of Thailand for the year 2024. Data are drawn from two principal sources: the Labor Force Survey (LFS) conducted by the National Statistical Office (NSO) and provincial economic statistics published by the National Economic and Social Development Council (NESDC). Variables derived from the LFS are calculated by the authors using individual-level microdata and the sampling weights provided by the NSO. The LFS is designed to produce representative labor market statistics at the provincial level, making it a suitable source for constructing provincial socioeconomic indicators. Because the survey is conducted quarterly, provincial estimates are first calculated separately for each quarter and then averaged across the four quarters of 2024 to reduce sampling variability and improve the stability of provincial estimates. GPP per capita is measured at constant prices, while non-agricultural GPP share is measured at nominal prices, consistent with the basis on which each series is published by NESDC.

Table 2 reports summary statistics for the ten indicators described above, based on the 2024 cross-section used for the main analysis.

Table 2. Summary statistics of provincial economic prosperity and distributional outcome indicators (2024, $n = 77$).

Variable	Mean	SD	Min	Max
Economic Prosperity				
GPP per capita (baht)	105,850.41	92,992.51	29,473.12	463,603.04
Educational attainment (%)	55.83	7.57	38.14	75.18
Urban population share (%)	35.46	16.77	11.28	100.00
Employment density (persons/km ²)	177.64	475.83	10.36	3493.73
Average monthly income (baht)	14,430.52	2834.32	9871.50	22,766.65
Non-agricultural GPP share (%)	76.57	12.52	47.09	99.96
Distributional Outcomes				
Gini coefficient	0.387	0.059	0.265	0.494
Economic vulnerability (%)	15.464	10.249	0.495	39.361
Informal employment share (%)	55.095	15.640	20.218	77.851
Household dependency ratio	0.941	0.181	0.413	1.332

Complete variable definitions, sample restrictions, and construction procedures for all ten indicators, including the treatment of zero income, the informal employment classification, and the use of 2023 poverty-line thresholds for 2024, are reported in Appendix A.

3.3. Ranking Methodology

3.3.1. Fundamental Concept of TOPSIS

The fundamental concept of TOPSIS is that the best solution is the one with the shortest distance to the positive ideal solution and the farthest distance from the negative ideal solution [58–60]. Accordingly, TOPSIS can be considered as a geometry-based method.

TOPSIS assumes that each attribute has a utility with a monotonic nature. In other words, each attribute takes either monotonically increasing or monotonically decreasing utility. TOPSIS divides the criteria into two groups, namely benefit/profit/positive and cost/loss/negative criteria. By definition, the positive ideal solution is composed of all best attribute values attainable, whereas the negative ideal solution is composed of all worst attribute values attainable. All criteria employed in this study satisfy this condition: the six prosperity indicators are treated as benefit criteria, for which higher values indicate higher economic prosperity, while the Gini coefficient, the economic vulnerability measure, the informal employment share, and the household dependency ratio are treated as cost criteria, for which lower values indicate more favorable distributional outcomes.

3.3.2. Steps in TOPSIS

TOPSIS consists of six steps as follows.

- (1) Construction of a normalized decision matrix, transforming indicator values measured in different units into dimensionless quantities comparable across criteria. An element r_{ij} of the normalized decision matrix R is defined as

$$r_{ij} = \frac{z_{ij}}{\left(\sum_{i=1}^m z_{ij}^2\right)^{1/2}}, \quad i = 1, \dots, m \text{ and } j = 1, \dots, n \quad (1)$$

- (2) Construction of a weighted normalized decision matrix. Equal weights were assigned to all criteria within each ranking because no established theoretical or policy basis exists for assigning different importance to the selected indicators. Equal weighting therefore provides a transparent baseline that avoids imposing differential priorities,

while Sections 4.4 and 4.5 assess sensitivity to alternative weighting schemes. The weighted normalized decision matrix is obtained as follows:

$$V = [v_{ij}]_{m \times n'} \quad (2)$$

where $v_{ij} = w_j r_{ij}$, $i = 1, \dots, m$, $j = 1, \dots, n$.

- (3) Determination of the positive ideal solution V^+ and the negative ideal solution V^- . Both solutions are defined as:

$$V^+ = \left\{ \left(\max_i v_{ij} \mid j \in C^+ \right), \left(\min_i v_{ij} \mid j \in C^- \right) \right\} = \{v_1^+, v_2^+, \dots, v_n^+\} \quad (3)$$

$$V^- = \left\{ \left(\min_i v_{ij} \mid j \in C^+ \right), \left(\max_i v_{ij} \mid j \in C^- \right) \right\} = \{v_1^-, v_2^-, \dots, v_n^-\} \quad (4)$$

where $C^+ = \{j \in \{1, \dots, n\} \mid \text{criterion } j \text{ is a benefit criterion}\}$ and $C^- = \{j \in \{1, \dots, n\} \mid \text{criterion } j \text{ is a cost criterion}\}$.

- (4) Calculation of separation measures using Euclidean distance. The separation between an alternative and the positive ideal solution V^+ , s_i^+ is

$$s_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2}, \quad i = 1, \dots, m \quad (5)$$

The separation between an alternative and the negative ideal solution V^- , s_i^- is

$$s_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2}, \quad i = 1, \dots, m \quad (6)$$

- (5) Calculation of the relative closeness to the positive ideal solution. The relative closeness of the alternative A_i with respect to V^+ , κ_i is defined as

$$\kappa_i = \frac{s_i^-}{s_i^+ + s_i^-}, \quad i = 1, \dots, m \quad (7)$$

- (6) Ranking of the preference order. The alternatives are preferred in accordance with the descending order of κ_i , i.e., the alternatives with higher κ_i 's are preferred to the ones with lower κ_i 's.

Figure 1 summarizes the complete TOPSIS procedure, showing how the initial decision matrix is normalized and weighted before the ideal solutions, separation measures, relative closeness coefficients, and final provincial rankings are determined.

Several limitations of the TOPSIS methodology should be acknowledged. First, TOPSIS closeness coefficients are relative to the specific set of alternatives being ranked, since the ideal and anti-ideal solutions are constructed from the best and worst observed values among the provinces included in the analysis. As a result, a province's score reflects its position relative to the other provinces in this study rather than an absolute, externally anchored quantity, and the method is, in principle, susceptible to the rank-reversal problem, whereby the relative ordering of two alternatives can change if the composition of the comparison set changes, even when the underlying data for those two alternatives remains unchanged [61]. Second, TOPSIS results are sensitive to the choice of normalization procedure used to render indicators comparable across different units and scales; different normalization methods, such as the vector normalization used in this study compared with linear min-max normalization, can in principle produce different closeness coefficients, and in some cases different relative rankings, even when applied to identical underlying data. Third, TOPSIS has a compensatory nature, meaning that a comparatively poor score on one indicator can be offset by a stronger score on another. Two provinces with similar overall

closeness coefficients may therefore have arrived at those scores through markedly different underlying profiles, one characterized by balanced performance across all indicators and another by strong performance on some indicators and weak performance on others. This compensatory property is a characteristic of TOPSIS rather than a limitation specific to this application. Relative closeness coefficients are interpreted as summary measures of overall relative standing rather than as evidence that provinces with the same coefficient have identical attribute values.

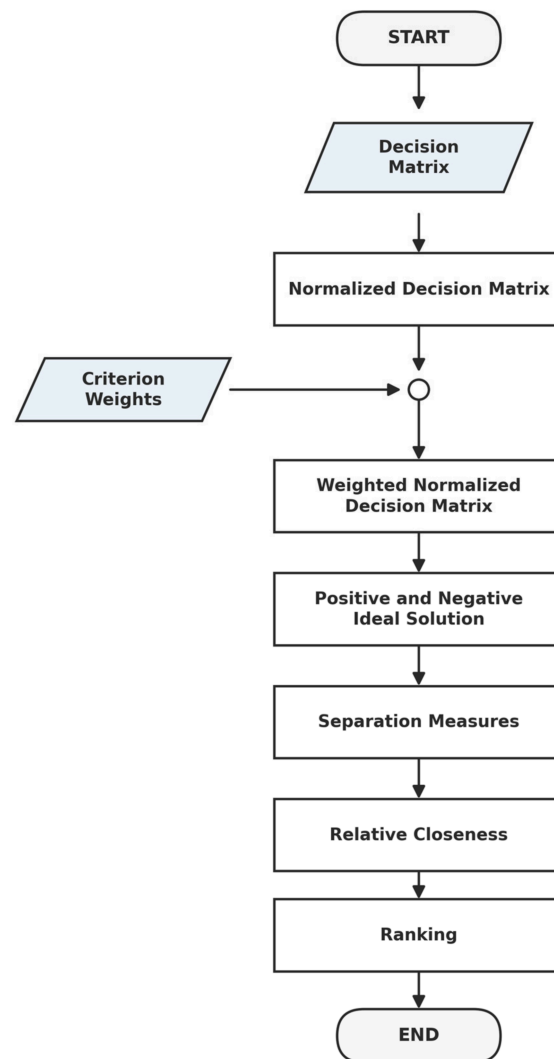


Figure 1. Flowchart summarizing the six steps of TOPSIS.

4. Results

This section presents the provincial rankings generated using TOPSIS. The analysis examines urban–regional disparities across two complementary dimensions: economic prosperity and distributional outcomes. The prosperity ranking captures differences in economic performance, human capital, urbanization, labor market outcomes, and structural transformation, while the distributional outcome ranking reflects variation in income inequality, economic vulnerability, informal employment, and demographic dependency. Because TOPSIS closeness coefficients are relative, descriptive measures of distance from the ideal solution rather than estimates drawn from a sampling distribution, differences between closely ranked provinces are interpreted descriptively rather than subjected to statistical significance testing.

4.1. Economic Prosperity Ranking

Figure 2 maps provincial economic prosperity scores, revealing a highly uneven geography of development marked by extreme urban primacy, a concentrated metropolitan–industrial core, substantial heterogeneity in the South, and persistent underperformance across much of the Northeast. Because Bangkok is a pronounced outlier, it is shown separately in yellow, while the remaining 76 provinces are displayed on a continuous blue gradient scaled to their own range to preserve visible variation. Higher values of the relative closeness coefficient (κ_i), defined in Equation (7), indicate greater economic prosperity. Regional summary statistics are reported in Table 3, while complete provincial rankings and within-region distributions appear in Figures A1 and A3. As discussed in Section 3.1, the six prosperity indicators are correlated but not redundant, so the composite ranking reflects several distinct dimensions of provincial economic capacity rather than one dominant variable.

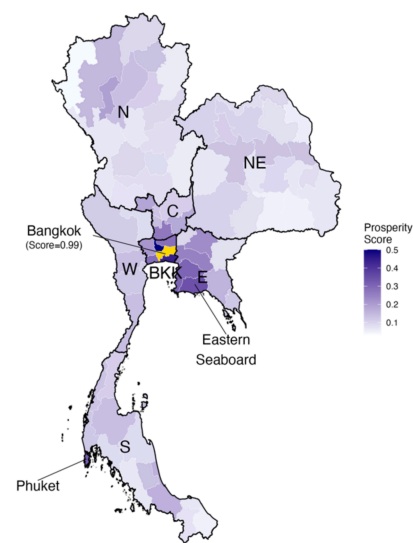


Figure 2. Spatial distribution of economic prosperity scores across Thai provinces, 2024. N = North; NE = Northeast; C = Central; W = West; E = East; S = South; BKK = Bangkok Metropolitan Region.

Table 3. Prosperity scores by region, 2024.

Region	Mean	SD	Median	Min	Max	Range	Skewness
Bangkok Metropolitan Region	0.453	0.285	0.366	0.209	0.990	0.781	1.252
East	0.198	0.098	0.195	0.080	0.343	0.263	0.210
Central	0.168	0.055	0.160	0.109	0.264	0.155	0.806
West	0.119	0.019	0.119	0.087	0.137	0.050	−0.605
South	0.116	0.068	0.099	0.052	0.322	0.270	2.072
North	0.096	0.038	0.089	0.036	0.191	0.155	0.892
Northeast	0.088	0.025	0.086	0.048	0.131	0.083	0.261

Note: Regions ordered by mean prosperity score (descending).

Beyond Bangkok, prosperity is concentrated within a broader metropolitan–industrial corridor encompassing the Bangkok Metropolitan Region and the Eastern Seaboard. Provinces surrounding Bangkok, together with major industrial centers such as Chon Buri and Rayong, consistently occupy the upper end of the ranking. This pattern is also reflected in regional averages: the Bangkok Metropolitan Region records the highest mean prosperity score (0.453), followed by the East (0.198). The concentration of high scores in these areas is consistent with agglomeration economies, market access, large labor markets, and the cumulative attraction of investment and skilled workers [46].

Figure 2 shows this corridor extending southeastward from Bangkok through Chachoengsao, Chon Buri, and Rayong. In contrast, much of the North and Northeast records substantially lower prosperity scores. This broader spatial pattern is consistent with peripheralization, in which infrastructure, investment, and economic activity remain concentrated in already advantaged locations, leaving other regions structurally disadvantaged [11].

Prosperity is not entirely confined to the metropolitan–industrial core. Phuket ranks fifth nationally with a score of 0.322, despite its distance from Bangkok and the Eastern Seaboard. Its position points to a distinct tourism-led pathway to prosperity based on internationally oriented services rather than industrial agglomeration. However, this pattern is not shared by tourism-oriented provinces more generally. Surat Thani, Phangnga, Krabi, Chiang Mai, and Chiang Rai all rank well below Phuket, suggesting that tourism specialization alone is insufficient to generate similarly high prosperity. Phuket’s performance more likely reflects the exceptional scale and intensity of its tourism economy, its long-established role as an international gateway, and its integration into global tourism networks.

Regional dispersion also differs substantially. The South records the widest range of prosperity scores outside the Bangkok Metropolitan Region, from 0.052 to 0.322, reflecting the coexistence of highly prosperous tourism centers and much weaker provinces, particularly in the southern border area. By contrast, the Northeast has both the lowest regional mean (0.088) and one of the narrowest ranges, indicating that low prosperity is widespread rather than driven by a small number of extreme cases.

The multidimensional prosperity ranking also differs meaningfully from a ranking based solely on GPP per capita. Although the two rankings are positively associated, their Spearman correlations are 0.71 in 2022, 0.71 in 2023, and 0.75 in 2024, indicating that provincial output per person does not fully reproduce the broader ordering of economic prosperity. In 2024, provinces shift by approximately 11–12 rank positions on average when the six-indicator framework is used in place of GPP per capita alone. For example, Krabi and Satun rank substantially higher by GPP per capita than by the composite measure, whereas Mukdahan, Phatthalung, and Kalasin rank considerably higher under the multidimensional framework. These differences show that output per person may either overstate or understate a province’s broader economic position when human capital, agglomeration, household income, and structural transformation are also considered. Summary statistics for this comparison are reported in Appendix A Table A7.

Overall, Thailand’s geography of prosperity is characterized by extreme urban primacy, a powerful metropolitan–industrial corridor, and uneven development across peripheral regions. Phuket demonstrates that alternative pathways exist, but these remain exceptional rather than broadly replicated.

4.2. Distributional Outcome Ranking

Figure 3 maps provincial distributional outcome scores, revealing a pronounced regional divide in which disadvantage is concentrated in the North and Northeast, while more favorable outcomes are clustered within Bangkok’s metropolitan–industrial corridor. Higher values of the relative closeness coefficient (κ_i), defined in Equation (7), indicate less favorable distributional outcomes, reflecting greater income inequality, economic vulnerability, informal employment, and household dependency. Regional summary statistics are reported in Table 4, while complete provincial rankings and within-region distributions appear in Figures A2 and A4. As discussed in Section 3.1, the four distributional indicators are likewise correlated but conceptually distinct, capturing different dimensions of distributional disadvantage rather than a single underlying factor.

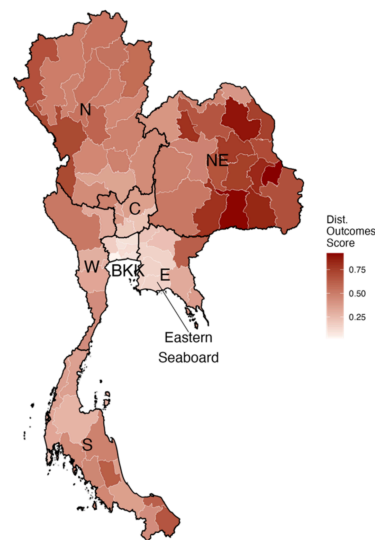


Figure 3. Spatial distribution of distributional outcome scores across Thai provinces, 2024. N = North; NE = Northeast; C = Central; W = West; E = East; S = South; BKK = Bangkok Metropolitan Region.

Table 4. Distributional outcome scores by region, 2024.

Region	Mean	SD	Median	Min	Max	Range	Skewness
Northeast	0.684	0.172	0.721	0.396	0.923	0.527	−0.366
North	0.513	0.089	0.497	0.346	0.708	0.362	0.578
South	0.430	0.137	0.437	0.180	0.662	0.482	0.163
West	0.362	0.091	0.324	0.283	0.515	0.232	0.856
Central	0.331	0.105	0.344	0.203	0.473	0.270	−0.037
East	0.277	0.159	0.220	0.154	0.617	0.463	1.314
Bangkok Metropolitan Region	0.104	0.048	0.099	0.029	0.176	0.147	−0.065

Note: Regions ordered by mean distributional outcome score (descending).

Table 4 shows a clear regional gradient. The Northeast records the least favorable distributional outcomes, with an average score of 0.684, followed by the North at 0.513. In contrast, the Bangkok Metropolitan Region has by far the most favorable average score at 0.104, while the East also performs relatively well at 0.277. Figure 3 reinforces this pattern, showing a broad concentration of disadvantage across the North and Northeast rather than isolated provincial pockets.

Bangkok and the surrounding metropolitan–industrial corridor perform particularly well. Samut Sakhon records the most favorable score nationally, followed by several provinces in the Bangkok Metropolitan Region and Eastern Seaboard. These provinces also rank highly in economic prosperity, suggesting that Thailand’s leading urban and industrial areas combine strong economic performance with comparatively favorable distributional outcomes.

Regional heterogeneity remains substantial in the South, where scores range from 0.180 to 0.662. Pattani and Narathiwat are among the least favorable provinces nationally, while several other southern provinces perform considerably better, indicating that the region encompasses markedly different development trajectories.

Comparing Figures 2 and 3 shows that prosperity and distributional outcomes are related but spatially distinct. Prosperity is concentrated within a relatively compact metropolitan–industrial core, whereas distributional disadvantage extends more broadly across the North and Northeast. The Spearman rank correlation between the two composite scores is $\rho = -0.675$ ($p < 0.001$, $n = 77$), indicating that more prosperous provinces generally exhibit more favorable distributional outcomes.

This result does not support a strong trade-off between provincial prosperity and favorable distributional outcomes in Thailand. Rather than combining high prosperity with greater disadvantage, Bangkok and the leading industrial provinces perform well across both dimensions. Although the result depends on the chosen framework, the distributional ranking incorporates inequality, economic vulnerability, labor market insecurity, and demographic pressure, reducing the likelihood that the observed pattern is driven by a single narrow measure of income inequality. Bangkok's favorable distributional score should not be interpreted as evidence that urban poverty or deprivation is absent; rather, it indicates comparatively favorable performance under the selected indicators, which account for province-specific poverty thresholds and informal employment but do not capture all dimensions of urban hardship, such as housing affordability.

Despite the strong association between prosperity and favorable distributional outcomes, several provinces depart from this general pattern. Chiang Mai, for example, combines relatively high prosperity with unfavorable distributional outcomes, while provinces such as Nakhon Nayok and Suphan Buri exhibit comparatively low prosperity but more favorable distributional outcomes. These exceptions reinforce the conclusion that the two rankings capture related but distinct dimensions of provincial development.

A joint classification based on the median prosperity and distributional outcome scores divides the provinces into four groups. Twenty-seven provinces combine relatively high prosperity with favorable distributional outcomes, while 12 combine high prosperity with unfavorable distributional outcomes. Among provinces below the median prosperity score, 11 exhibit relatively favorable distributional outcomes and 27 face disadvantages on both dimensions. A summary of the classification is reported in Appendix A Table A5.

4.3. Ranking Evolutions

The 2024 TOPSIS rankings were reconstructed for 2022 and 2023 to assess temporal stability. Complete provincial scores are reported in Supplementary Table S1, while Appendix A Tables A3 and A4 report rank correlations and quartile-stability measures for both the original annual samples (Panel A) and the harmonized employee-only samples (Panel B).

The prosperity ranking is highly stable across years. Pairwise Spearman correlations exceed 0.98, and 63 of the 77 provinces (81.8%) remain in the same quartile in all three years. Bangkok, Nonthaburi, Samut Prakan, and Rayong occupy the top four positions throughout, while the broader concentration of high-ranking provinces in the Bangkok Metropolitan Region and Eastern Seaboard remains unchanged.

Temporal comparisons of distributional outcomes require harmonized income samples because the LFS expanded income reporting in 2024 from employees only to all employed persons, including self-employed workers and employers. When the 2024 indicators are reconstructed using the employee-only sample used in 2022 and 2023, the Spearman correlations are 0.912 for 2022–2024 and 0.946 for 2023–2024, while 50 provinces (64.9%) remain in the same quartile across all three years. The broad spatial pattern also remains stable within the harmonized employee-only series, with relatively favorable outcomes concentrated in the Bangkok Metropolitan Region and the surrounding industrial corridor and less favorable outcomes concentrated mainly in the South. This pattern differs somewhat from the main 2024 ranking based on all employed persons, in which disadvantage is more strongly concentrated in the North and Northeast.

The reduced comparability of the unadjusted 2024 distributional ranking should not be interpreted as a weakness of the 2024 data. Rather, it reflects an improvement in the coverage of the LFS income module. By extending income reporting beyond employees to include self-employed workers and employers, the 2024 survey provides a more compre-

hensive representation of income distribution among employed persons. Because these groups exhibit greater income dispersion, their inclusion affects both the Gini coefficient and the economic vulnerability measure. The 2024 indicators may therefore provide a more representative basis for assessing provincial distributional outcomes, although they are not directly comparable with estimates constructed from the narrower employee-only samples available in 2022 and 2023.

Overall, the prosperity ranking is exceptionally stable, while the distributional ranking remains reasonably robust once differences in income coverage are accounted for.

4.4. Robustness to Alternative Method, Normalization, and Weighting Specifications

The robustness of the rankings is further assessed using alternative normalization procedures, weighting schemes, and multicriteria decision-making methods. The vector normalization adopted in the main analysis is compared with min–max normalization [62], while equal weighting is compared with entropy weighting. Two alternative MCDM methods, MOORA [63] and CODAS [64], are also considered, together with a PCA-based composite index.

These choices yield nine specifications. M1 is the baseline specification used in the main analysis, consisting of TOPSIS with vector normalization and equal weights. M2 applies TOPSIS with vector normalization and entropy weights; M3 and M4 apply TOPSIS with min–max normalization and equal and entropy weights, respectively; M5 and M6 apply MOORA with equal and entropy weights; M7 and M8 apply CODAS with equal and entropy weights; and M9 is the PCA-based composite index.

Provincial rankings were recomputed under all nine specifications for both prosperity and distributional outcomes in 2022, 2023, and 2024. Consistency across specifications was evaluated using pairwise Spearman rank correlations, producing a 9×9 correlation matrix for each ranking and year.

Tables 5 and 6 report the full Spearman rank correlation matrices among the nine method specifications for 2024, for the economic prosperity and distributional outcome rankings, respectively. Across all six ranking-year combinations (both rankings, 2022–2024), every pairwise correlation exceeds 0.98, indicating that the provincial rankings are highly robust to alternative normalization procedures, weighting schemes, and aggregation methods. The baseline specification, M1, also has a higher average correlation with the other eight specifications than the PCA-based index, M9, in five of the six ranking-year comparisons. Provincial rank consistency across all nine specifications is illustrated directly in Appendix A Figures A5 and A6, where each province holds a similar color across all nine columns, visually confirming the stability reported above.

Table 5. Spearman rank correlation matrix among nine method specifications (M1–M9), economic prosperity ranking, 2024.

	M1	M2	M3	M4	M5	M6	M7	M8	M9
M1	1.000	0.993	0.993	0.995	0.997	0.994	0.996	0.996	0.994
M2	0.993	1.000	0.991	0.994	0.994	0.997	0.992	0.996	0.992
M3	0.993	0.991	1.000	0.995	0.995	0.993	0.997	0.993	0.998
M4	0.995	0.994	0.995	1.000	0.996	0.995	0.995	0.997	0.995
M5	0.997	0.994	0.995	0.996	1.000	0.995	0.997	0.997	0.996
M6	0.994	0.997	0.993	0.995	0.995	1.000	0.993	0.996	0.993
M7	0.996	0.992	0.997	0.995	0.997	0.993	1.000	0.995	0.996
M8	0.996	0.996	0.993	0.997	0.997	0.996	0.995	1.000	0.994
M9	0.994	0.992	0.998	0.995	0.996	0.993	0.996	0.994	1.000

Table 6. Spearman rank correlation matrix among nine method specifications (M1–M9), distributional outcome ranking, 2024.

	M1	M2	M3	M4	M5	M6	M7	M8	M9
M1	1.000	0.998	0.996	0.998	0.998	0.999	0.996	0.998	0.996
M2	0.998	1.000	0.994	0.997	0.996	0.998	0.994	0.998	0.994
M3	0.996	0.994	1.000	0.996	0.997	0.996	0.997	0.995	0.999
M4	0.998	0.997	0.996	1.000	0.997	0.998	0.995	0.998	0.996
M5	0.998	0.996	0.997	0.997	1.000	0.998	0.997	0.997	0.998
M6	0.999	0.998	0.996	0.998	0.998	1.000	0.995	0.999	0.995
M7	0.996	0.994	0.997	0.995	0.997	0.995	1.000	0.995	0.997
M8	0.998	0.998	0.995	0.998	0.997	0.999	0.995	1.000	0.995
M9	0.996	0.994	0.999	0.996	0.998	0.995	0.997	0.995	1.000

These results indicate that the study’s substantive conclusions—including the spatial concentration of prosperity, the geography of distributional disadvantage, and the temporal stability of the rankings—are not artifacts of the selected normalization procedure, weighting scheme, or MCDM method. Rather, they reflect persistent underlying patterns in the provincial data.

4.5. Robustness to Random Weight Perturbation

Section 4.4 shows that the rankings are robust to alternative normalization procedures, weighting schemes, and MCDM aggregation methods considered as discrete alternatives. As a further, complementary check, the sensitivity of the baseline ranking (M1) to continuous variation in the indicator weights was assessed directly. For each of the two rankings, the weight assigned to every indicator was randomly perturbed within $\pm 20\%$ of its baseline equal-weight value and the resulting weights were renormalized to sum to one; TOPSIS was then recomputed under the perturbed weight vector. This procedure was repeated 1000 times independently for the economic prosperity ranking (six indicators) and the distributional outcome ranking (four indicators), using 2024 data, following established Monte Carlo approaches to weight-sensitivity testing in additive multicriteria decision-making methods [65,66], an approach also applied in other multicriteria decision contexts [67,68].

For each of the 1000 simulations, the Spearman rank correlation (ρ) between the perturbed-weight ranking and the baseline equal-weight ranking was calculated, producing a distribution of 1000 ρ values for each ranking. For the economic prosperity ranking, the simulated ρ values had a mean of 0.975 (SD = 0.001), ranging from a minimum of 0.970 to a maximum of 0.978. For the distributional outcome ranking, the simulated ρ values had a mean of 0.968 (SD = 0.001), ranging from a minimum of 0.966 to a maximum of 0.970. Every one of the 2000 simulated rankings therefore correlates with its respective baseline ranking at $\rho > 0.96$. These results indicate that the provincial rankings are not sensitive to the precise weighting scheme within a plausible range of weight variation, reinforcing the robustness established in Section 4.4.

4.6. Spatial Autocorrelation

The spatial patterns shown in Figures 2 and 3 suggest that provincial prosperity and distributional outcomes are geographically structured rather than randomly distributed. To assess this formally, Global Moran’s I was calculated using the 2024 TOPSIS scores and queen-contiguity spatial weights. Provinces sharing either a boundary or a vertex were treated as neighbors, with a k-nearest-neighbor fallback used for island provinces without contiguous neighbors. Statistical significance was assessed using 999 random permutations.

Both rankings exhibit statistically significant positive spatial autocorrelation. Global Moran's I is 0.492 for economic prosperity and 0.703 for distributional outcomes, with permutation-based p -values of 0.001 in both cases. These positive values indicate that provinces with similar scores tend to be located near one another rather than being randomly distributed across Thailand. The larger Moran's I for distributional outcomes suggests that distributional advantage and disadvantage form a more geographically continuous pattern than economic prosperity. Prosperity is concentrated in a relatively compact metropolitan core, whereas distributional outcomes exhibit broader regional clustering.

Local Indicators of Spatial Association (LISA) (Queen contiguity spatial weights with k -nearest-neighbor fallback for island provinces; statistical significance based on 999 permutations ($p < 0.05$)) identify the provinces contributing to these global patterns. For economic prosperity (Figure 4), the significant High–High cluster comprises Bangkok, Samut Prakan, Nonthaburi, Pathum Thani, Nakhon Pathom, Samut Sakhon, and Chachoengsao. These provinces combine relatively high prosperity scores with similarly high scores in neighboring provinces, indicating that Thailand's principal prosperity cluster extends beyond Bangkok into the surrounding metropolitan area and eastward to Chachoengsao.

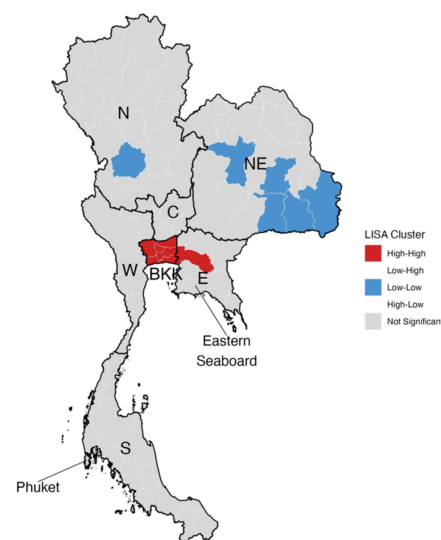


Figure 4. LISA cluster map for economic-prosperity TOPSIS scores, 2024. N = North; NE = Northeast; C = Central; W = West; E = East; S = South; BKK = Bangkok Metropolitan Region.

Significant Low–Low prosperity clusters are found in Surin, Si Sa Ket, Ubon Ratchathani, Khon Kaen, Roi Et, and Kamphaeng Phet. These provinces have relatively low prosperity scores and are surrounded by provinces with similarly low scores. The results indicate that low prosperity is spatially concentrated in parts of the Northeast, although the inclusion of Kamphaeng Phet shows that significant local clustering is not confined exclusively to that region. No statistically significant High–Low or Low–High prosperity outliers are identified.

The spatial pattern is more extensive for distributional outcomes (Figure 5). Because higher distributional outcome scores indicate less favorable conditions, High–High classifications represent clusters of disadvantage. Fourteen provinces form a significant High–High cluster: Buri Ram, Surin, Si Sa Ket, Ubon Ratchathani, Yasothorn, Amnat Charoen, Khon Kaen, Udon Thani, Maha Sarakham, Roi Et, Kalasin, Sakon Nakhon, Nakhon Phanom, and Mukdahan. This cluster covers a large and geographically connected portion of the Northeast, indicating that unfavorable distributional conditions are embedded within a broader regional pattern rather than confined to isolated provinces.

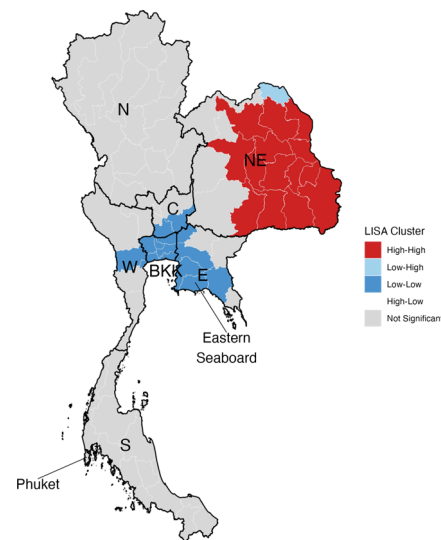


Figure 5. LISA cluster map for distributional outcome TOPSIS scores, 2024. N = North; NE = Northeast; C = Central; W = West; E = East; S = South; BKK = Bangkok Metropolitan Region.

Significant Low–Low distributional clusters, representing favorable outcomes surrounded by similarly favorable neighboring provinces, are concentrated in the Bangkok Metropolitan Region and the central–eastern industrial corridor. They include Bangkok, Samut Prakan, Nonthaburi, Pathum Thani, Phra Nakhon Si Ayutthaya, Saraburi, Chon Buri, Rayong, Chanthaburi, Chachoengsao, Nakhon Nayok, Ratchaburi, Nakhon Pathom, Samut Sakhon, and Samut Songkhram. The spatial extent of this cluster indicates that favorable distributional outcomes are not limited to Bangkok itself but extend across a wider metropolitan and industrial zone.

Buang Kan is the only statistically significant spatial outlier in the distributional analysis. It is classified as Low–High, indicating that the province has comparatively favorable distributional outcomes despite being surrounded by provinces with less favorable conditions. No significant High–Low distributional outliers are identified. Provinces with statistically significant LISA classifications are reported in Appendix A Table A6.

Taken together, the global and local results reinforce the interpretation of Thailand’s provincial disparities as spatially concentrated rather than independent province-level differences. Prosperity is clustered within a relatively compact Bangkok-centered metropolitan area, while low prosperity appears in smaller pockets, particularly in the Northeast. Distributional outcomes show a more clearly regionalized structure, with favorable conditions extending across the metropolitan–industrial corridor and disadvantage concentrated across much of the Northeast. These results identify spatial association rather than causal spillovers, but they demonstrate that provincial development conditions are closely related to the wider geographic context in which provinces are located.

5. Implications for Policy and Spatial Decision-Making

The principal policy value of the rankings lies in providing a more differentiated basis for comparing provincial economic conditions in Thailand. Provincial performance is commonly assessed using individual indicators, particularly GPP per capita, or summarized at the level of broad administrative regions. Although these measures are useful, they may conceal important differences in human capital, spatial agglomeration, labor market outcomes, structural transformation, inequality, economic vulnerability, informal employment, and household dependency. By separating economic prosperity from distributional outcomes, the present framework provides a broader basis for identifying these differences.

The comparison with GPP per capita demonstrates that the multidimensional prosperity ranking is not merely a more detailed presentation of the same provincial ordering. Although the two rankings are positively associated (Spearman $\rho = 0.71$ – 0.75 across 2022–2024; Appendix A Table A7), they differ substantially in the relative positions assigned to individual provinces. Several provinces move markedly once educational attainment, urbanization, employment density, household income, and structural transformation are considered alongside output per person. GPP per capita alone may therefore either overstate or understate a province's broader economic position. This distinction is particularly important when provincial rankings are used to identify lagging areas, compare development performance, or select provinces for more detailed policy analysis.

The separate prosperity and distributional outcome rankings also caution against treating provincial development as a single continuum from developed to lagging. Provinces with similar levels of prosperity may face very different distributional conditions, while provinces with similar distributional scores may differ substantially in productive capacity. The joint classification summarized in Appendix A Table A5 provides a practical way to distinguish these combinations and to identify whether a province's principal concern lies in weak economic foundations, unfavorable distributional conditions, or both.

For example, a province combining low prosperity with unfavorable distributional outcomes warrants examination of both its productive capacity and the sources of socioeconomic vulnerability. By contrast, a province combining high prosperity with unfavorable distributional outcomes requires analysis of why stronger economic performance is not translating into more broadly favorable conditions. Similarly, provinces with low prosperity but relatively favorable distributional outcomes may require policies that expand economic opportunity without weakening their existing distributional position. The classification therefore guides the diagnostic questions to be investigated rather than mechanically prescribing a particular intervention.

The four groups nevertheless imply different broad policy priorities. High-prosperity provinces with favorable distributional outcomes require attention to sustaining productivity while managing congestion, affordability, and emerging inequalities. High-prosperity provinces with unfavorable distributional outcomes call for stronger labor formalization, social protection, and measures that broaden access to economic opportunities. Low-prosperity provinces with relatively favorable distributional outcomes require productivity-enhancing investment, connectivity, human-capital development, and economic diversification without undermining their existing distributional position. Provinces disadvantaged on both dimensions require coordinated place-based interventions combining productive investment with employment support, human-capital development, and protection for economically vulnerable households.

The rankings should consequently be used as an initial screening and benchmarking tool rather than as a direct rule for allocating resources or selecting policies. A composite score summarizes a province's relative position but does not identify which individual indicator is primarily responsible for that position. Policy analysis should therefore proceed from the overall ranking to the underlying indicator profile. An unfavorable distributional score may be driven mainly by income inequality, economic vulnerability, informal employment, household dependency, or a combination of these factors. Likewise, a weak prosperity score may reflect low output, limited human capital, weak agglomeration, low household income, or limited structural transformation. Examining the component indicators is necessary before drawing conclusions about the appropriate policy response.

The framework may also improve the spatial targeting and evaluation of public programs. Policies in Thailand are often designed around administrative regions or implemented across provinces using common eligibility criteria. The results show, however,

that provinces within the same region may occupy very different positions in the two rankings. Southern Thailand provides a particularly clear example, encompassing Phuket's high-prosperity tourism economy as well as provinces facing substantial economic and distributional disadvantage. Provincial benchmarking can therefore complement regional planning by identifying where common regional policies may require different priorities, implementation arrangements, or evaluation criteria across provinces.

The rankings also provide a basis for examining whether public investment and policy attention are aligned with measured provincial conditions. Government agencies and researchers could compare the geographic distribution of infrastructure spending, social programs, workforce initiatives, or regional-development projects with the prosperity and distributional profiles reported here. Such comparisons would not establish whether existing allocations are optimal, but they could reveal mismatches between policy resources and provincial conditions and identify provinces requiring more detailed investigation.

The present framework complements rather than replaces the Provincial SDG Index. The SDG Index evaluates a broad conception of sustainable development across economic, social, environmental, and institutional dimensions. The rankings developed here address a narrower question by isolating economic prosperity and distributional outcomes. They are therefore more directly suited to analyses concerned with provincial economic capacity, labor market conditions, and the distribution of economic disadvantage. A province may perform favorably under the SDG framework while ranking less favorably in economic prosperity, or vice versa, because the two systems are designed to assess different concepts.

More generally, the study demonstrates the importance of matching a composite indicator to the policy question it is intended to address. GDP per capita, poverty measures, competitiveness indices, sustainability indices, and multidimensional prosperity rankings may assign different positions to the same province because each captures a different aspect of development. No single ranking should therefore be treated as a universal measure of provincial performance. The value of the present approach lies in making its analytical focus explicit and in separating economic capacity from distributional disadvantage.

The framework can also be updated as new provincial data become available. Repeated calculation of the rankings would allow analysts to assess whether provinces are improving in prosperity, distributional outcomes, or both, while changes in the underlying indicators could help identify the sources of movement. The rankings may therefore serve not only as cross-sectional benchmarks but also as tools for monitoring provincial trajectories and evaluating whether spatial disparities are narrowing or becoming more persistent.

The approach may also be adapted to other countries with comparable subnational economic and household data. Its transferability lies in the separation of economic capacity from distributional outcomes rather than in the specific indicators used in Thailand. Applications in other settings would need to reconsider the relevant spatial units, indicator definitions, data availability, and institutional context rather than adopt the present six-and-four indicator structure unchanged.

Overall, the findings support the use of multidimensional provincial benchmarking as a complement to existing economic statistics, administrative-region comparisons, and sustainability indices. By distinguishing economic prosperity from distributional outcomes, the framework provides a more precise basis for comparing provinces, diagnosing spatial disparities, targeting further analysis, and assessing whether public policies are aligned with provincial conditions.

6. Conclusions

This study develops separate TOPSIS rankings of economic prosperity and distributional outcomes for all 77 Thai provinces. The prosperity ranking combines six indicators

covering economic output, human capital, spatial agglomeration, labor market outcomes, and structural transformation, while the distributional ranking combines four indicators capturing income inequality, economic vulnerability, informal employment, and household dependency. Separating these dimensions makes it possible to distinguish the strength of a province's economic foundations from the extent of socioeconomic disadvantage experienced by its residents.

The results reveal a strongly uneven geography of provincial development. Economic prosperity is concentrated in Bangkok, the surrounding metropolitan region, and the Eastern Seaboard, which together form a dominant metropolitan–industrial corridor. Phuket represents a distinct tourism-led pathway outside this core, although similarly favorable outcomes are not observed across tourism-oriented provinces more generally. Low prosperity remains widespread across much of the Northeast, while the South exhibits substantial internal heterogeneity.

Distributional outcomes display a related but distinct spatial pattern. Favorable outcomes are concentrated primarily within the metropolitan–industrial corridor, whereas disadvantage is more prevalent across the North and Northeast. The strong but imperfect association between the two rankings confirms that economic prosperity and distributional outcomes should not be treated as interchangeable measures of provincial development. The comparison with GPP per capita reinforces this point: output per person alone does not reproduce the multidimensional prosperity ranking and may substantially overstate or understate the broader economic position of individual provinces.

The findings are robust across several dimensions. The prosperity ranking remains exceptionally stable from 2022 to 2024. Once differences in LFS income coverage are harmonized, the distributional ranking also exhibits substantial temporal stability. Rankings are likewise highly consistent across alternative normalization procedures, weighting schemes, MCDM methods, and a PCA-based index. Global Moran's *I* and local spatial statistics further confirm that the geographic concentrations identified in the maps reflect statistically significant spatial clustering rather than visual patterns alone.

Several limitations remain. The rankings depend on the selected indicators and cannot capture every relevant dimension of provincial development because comparable subnational data are unavailable for some factors. TOPSIS is compensatory, so strong performance on one indicator can offset weakness on another, and the resulting closeness coefficients are relative to the provinces included in the comparison rather than absolute measures of development. Although the sensitivity analyses indicate that the rankings are highly stable, equal weighting and vector normalization remain methodological choices rather than uniquely correct specifications. The rankings should therefore be interpreted as diagnostic summaries of relative provincial standing and should be examined alongside the underlying indicator profiles. In addition, the analysis identifies associations and spatial patterns but does not establish the causal mechanisms producing provincial prosperity or distributional disadvantage.

Despite these limitations, the study provides a systematic and transparent framework for provincial benchmarking in Thailand. It demonstrates that multidimensional economic assessment yields materially different information from rankings based on GPP per capita alone and that separating prosperity from distributional outcomes improves the interpretation of spatial disparities. The framework complements broader sustainability measures such as the Provincial SDG Index by providing a more focused basis for economic and distributional analysis. More broadly, it offers a replicable approach for monitoring provincial trajectories, identifying areas requiring closer investigation, and supporting more differentiated spatial analysis and decision-making.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/urbansci10080449/s1>, Table S1: Provincial TOPSIS scores and rankings for economic prosperity and distributional outcomes, 2022–2024. Table S2: Provincial criteria variables for economic prosperity and distributional outcomes rankings, 2022–2024.

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Abbreviations

The following abbreviations are used in this manuscript:

CICI	China Integrated City Index
GPP	Gross Provincial Product
LFS	Labor Force Survey
LISA	Local Indicators of Spatial Association
MCDM	Multi-Criteria Decision Making
NESDC	National Economic and Social Development Council
NSO	National Statistical Office
NUTS	Nomenclature of Territorial Units for Statistics
PCI	Provincial Competitiveness Index
SDG	Sustainable Development Goal
TOPSIS	Technique for Order Preference by Similarity to the Ideal Solution

Appendix A

Appendix A.1 Economic Prosperity Indicators

1. GPP per capita. Real gross provincial product per capita, measured at constant prices. Source: NESDC.
2. Educational attainment. Share of the working-age population (16–65) with secondary or tertiary education. Source: LFS.
3. Urban population share. Share of the working-age population (16–65) residing in municipal areas. Source: LFS.

4. Employment density. Number of working-age employed persons per square kilometer of provincial land area. Because provincial boundaries are administrative rather than functional economic areas, this measure is partly sensitive to differences in provincial land area and may favor geographically compact provinces. Source: LFS and NESDC.
5. Average monthly income. Average real monthly income among working-age income earners. Source: LFS.
6. Non-agricultural GPP share. Non-agricultural share of gross provincial product, measured at nominal prices. Source: NESDC.

Appendix A.2 Distributional Outcome Indicators

1. Gini coefficient. Gini coefficient of income distribution, calculated among working-age individuals reporting positive income. Individuals with zero reported income, who account for approximately 2.6 percent of the working-age labor force sample, are excluded because the indicator is intended to measure the distribution of income among earners. The Palma ratio was also considered as an alternative measure of inequality but was excluded because it was highly correlated with the Gini coefficient ($r = 0.94$), adding little distinct information while increasing the weight assigned to inequality. Source: LFS.
2. Economic vulnerability. Share of income earners, including those with zero income, with income below twice the province-specific poverty line. Because province-level poverty lines for 2024 had not been published at the time of the analysis, the 2023 provincial thresholds are carried forward to 2024; the national poverty line rose by only 1.1 percent between 2023 and 2024. Source: LFS; NESDC.
3. Informal employment share. Share of working-age employed persons in informal employment. Informal workers are defined as own-account workers without employees, unpaid family workers, workers engaged by multiple employers or on a contract basis, and members of producers' cooperatives or groups. Formal workers comprise employers and government, state-enterprise, and private-sector employees. Source: LFS.
4. Household dependency ratio. Ratio of weighted non-working household members to weighted employed working-age household members. Source: LFS.

Table A1. Pairwise Correlations Among Economic Prosperity Indicators.

Variable	(1)	(2)	(3)	(4)	(5)
(1) GPP per capita					
(2) Educational attainment	0.629				
(3) Urban population share	0.524	0.428			
(4) Employment density	0.551	0.486	0.582		
(5) Average monthly income	0.618	0.669	0.493	0.496	
(6) Non-agricultural GPP share	0.664	0.592	0.470	0.473	0.326

Note: Pearson correlation coefficients, computed across all 77 Thai provinces using 2024 data.

Table A2. Pairwise Correlations Among Distributional Outcomes Indicators.

Variable	(1)	(2)	(3)
(1) Gini coefficient			
(2) Economic vulnerability	0.717		
(3) Informal employment share	0.590	0.660	
(4) Household dependency ratio	0.481	0.627	0.622

Note: Pearson correlation coefficients, computed across all 77 Thai provinces using 2024 data.

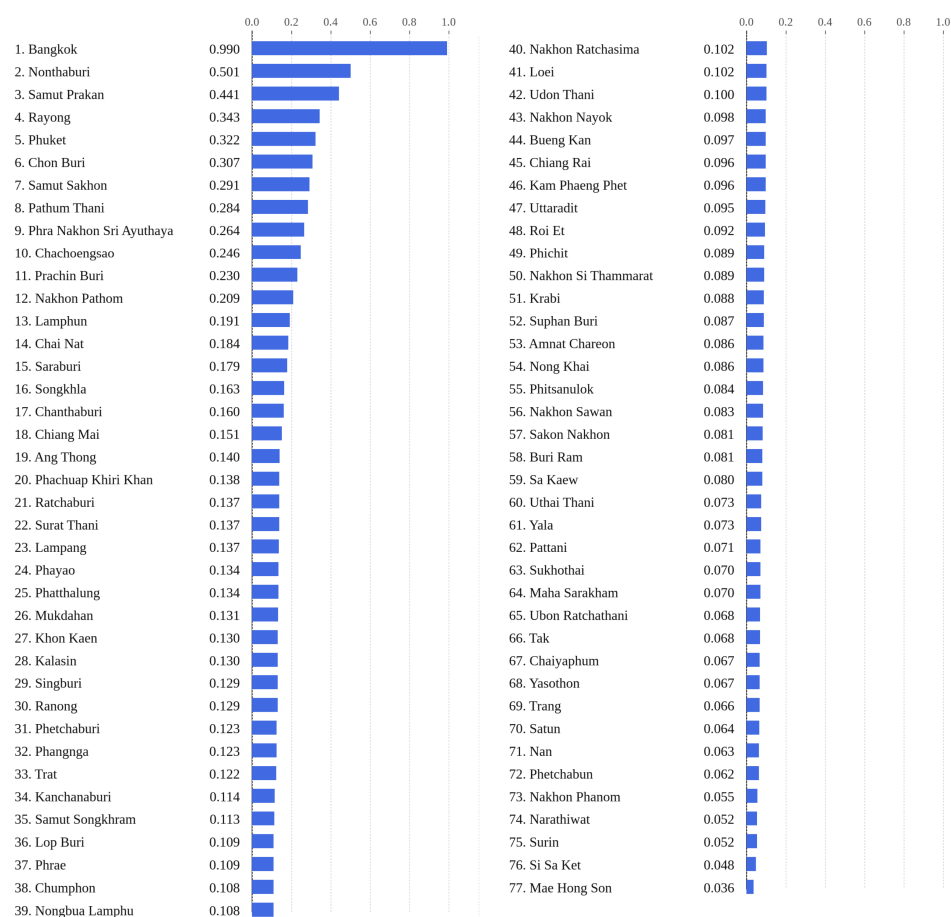


Figure A1. TOPSIS-based ranking of Thai provinces by economic prosperity, 2024.

Table A3. Spearman Rank Correlations Across Years.

Dimension	2022 vs. 2023	2022 vs. 2024	2023 vs. 2024
Panel A. Rankings based on available income samples			
Economic prosperity	0.995	0.981	0.982
Distributional outcomes	0.943	0.652	0.652
Panel B. Rankings based on harmonized employee-only samples			
Economic prosperity	0.995	0.991	0.992
Distributional outcomes	0.943	0.912	0.946

Note: Spearman rank correlation coefficients computed across all 77 Thai provinces. Panel A uses the income sample available in each year (employees only in 2022 and 2023; all employed persons in 2024); Panel B restricts 2024 to the employee-only sample used in 2022 and 2023 for direct comparability. All correlations are statistically significant at the 1% level ($p < 0.001$).

Table A4. Quartile Stability Across Years.

Dimension	Provinces in Same Quartile (All 3 Years)	Share (%)
Panel A. Rankings based on available income samples		
Economic prosperity	63 of 77	81.8
Distributional outcomes	29 of 77	37.7
Panel B. Rankings based on harmonized employee-only samples		
Economic prosperity	67 of 77	87.0
Distributional outcomes	50 of 77	64.9

Note: A province is classified as stable if it falls in the same quartile in all three years (2022, 2023, and 2024). Quartiles are equal-sized groups (Q1–Q4) assigned separately by dimension and year. Panel A uses the income sample available in each year (employees only in 2022 and 2023; all employed persons in 2024); Panel B restricts 2024 to the employee-only sample used in 2022 and 2023 for direct comparability.

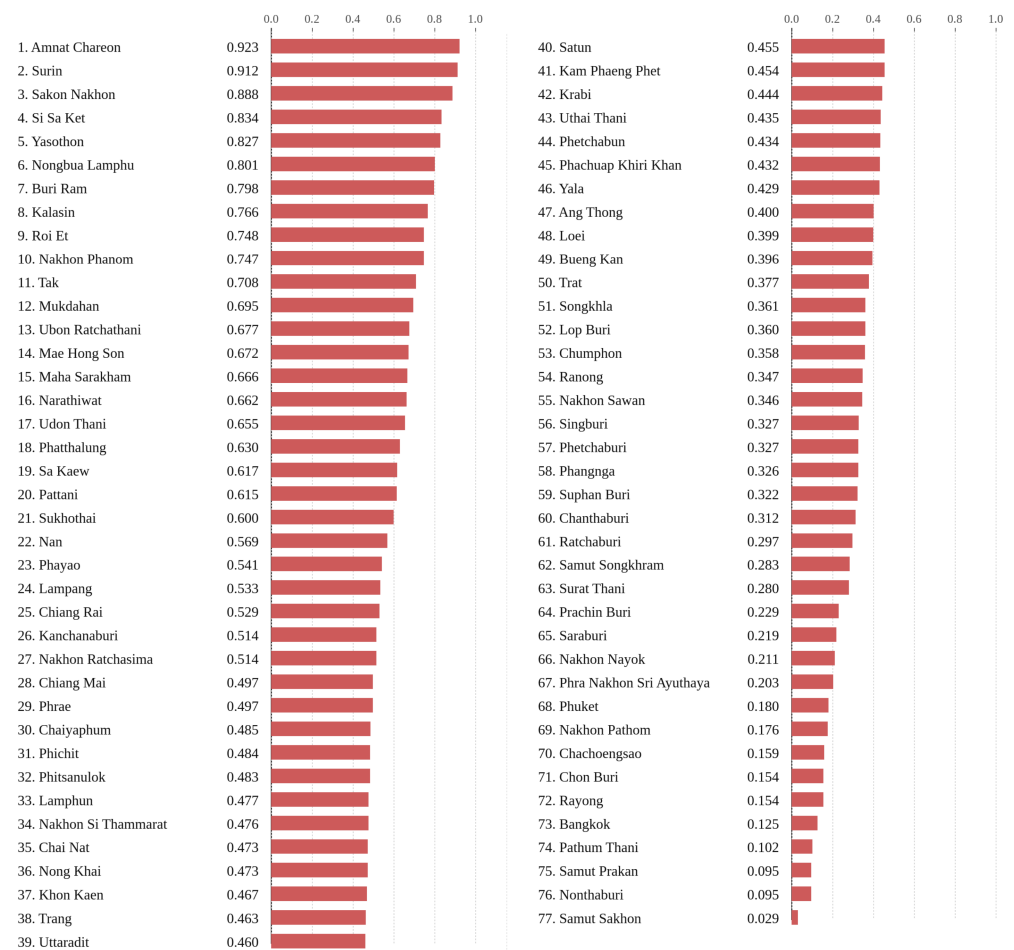


Figure A2. TOPSIS-based ranking of Thai provinces by distributional outcomes, 2024.

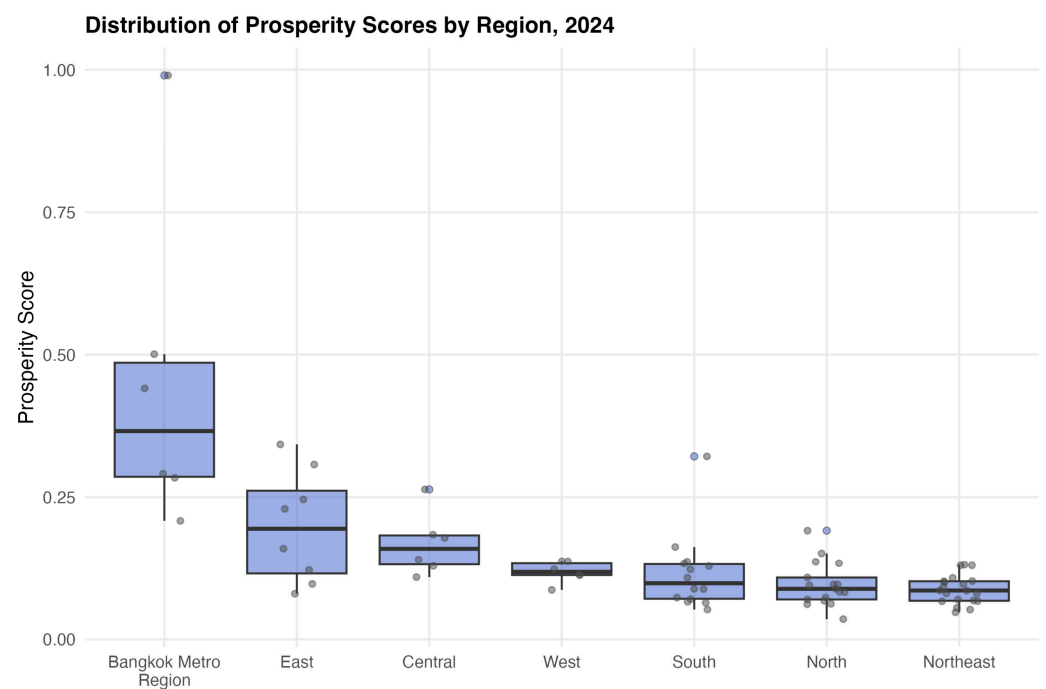


Figure A3. Distribution of provincial prosperity scores by region, 2024. Boxes show the interquartile range and median; points show individual province scores.

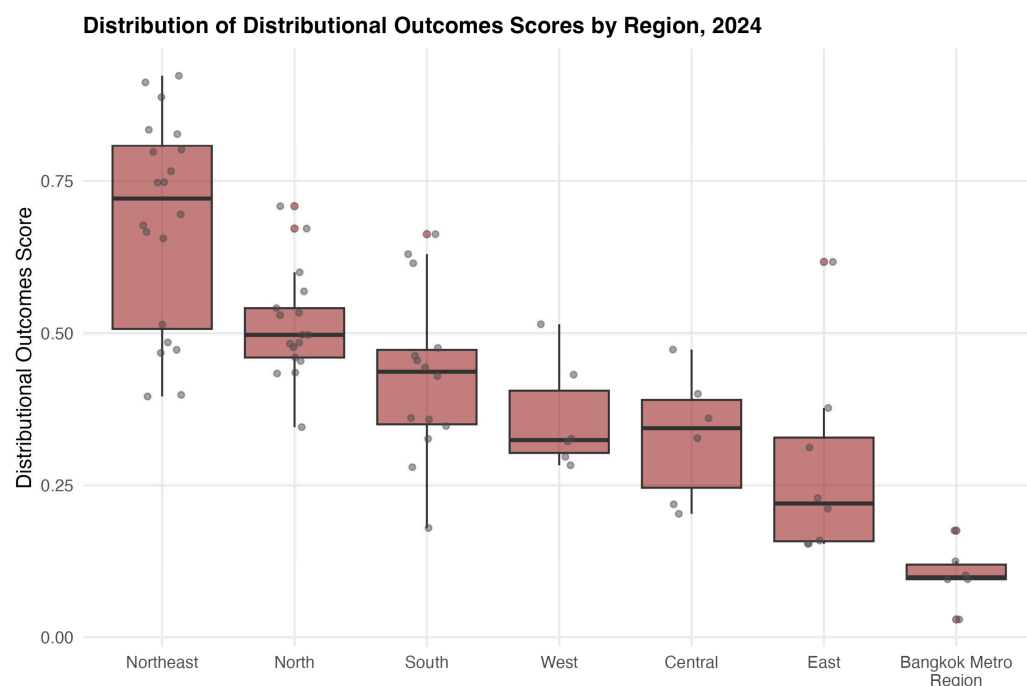


Figure A4. Distribution of provincial distributional outcomes scores by region, 2024. Boxes show the interquartile range and median; points show individual province scores.

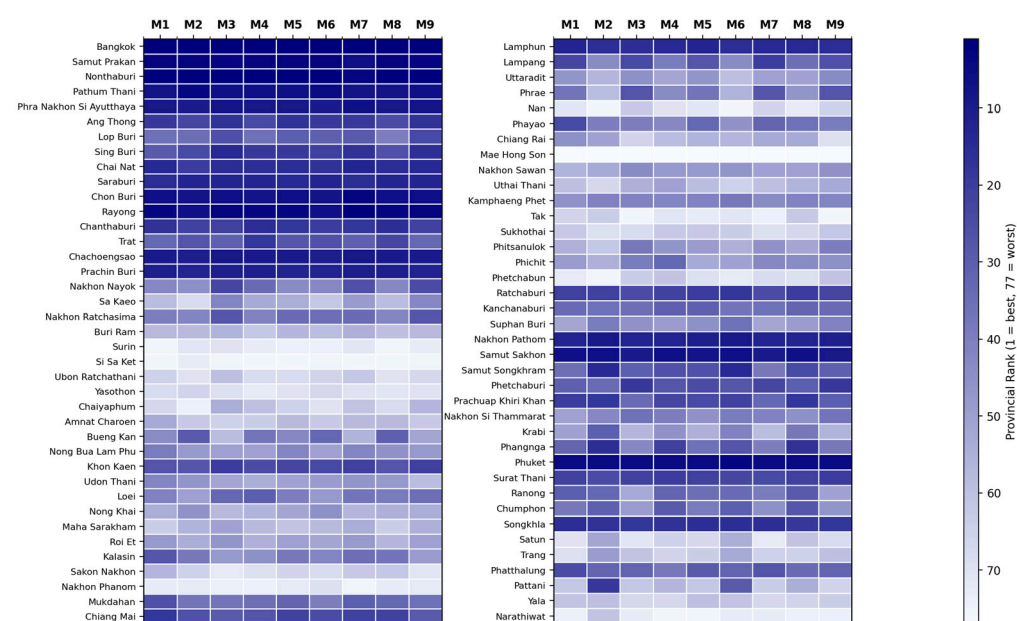


Figure A5. Provincial rank consistency across nine method specifications (M1–M9), economic prosperity ranking, 2024.

Table A5. Joint classification of provincial prosperity and distributional outcomes, 2024.

Quadrant	n	Predominant Regions
High Prosperity/Favorable Distribution	27	Bangkok Metropolitan Region, East, Central, South, West
High Prosperity/Unfavorable Distribution	12	North, Northeast
Low Prosperity/Favorable Distribution	11	North, Northeast, South
Low Prosperity/Unfavorable Distribution	27	Northeast, North

Note: Classification based on median splits of the 2024 prosperity and distributional outcomes scores.

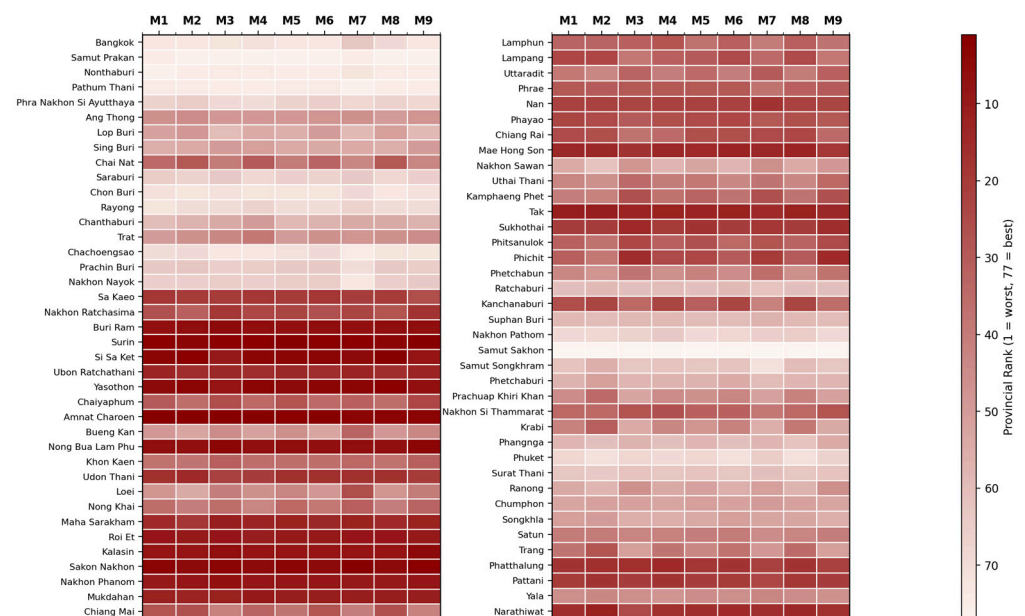


Figure A6. Provincial rank consistency across nine method specifications (M1–M9), distributional outcomes ranking, 2024.

Table A6. Provinces with statistically significant LISA classifications.

Province	Region	Prosperity	Distributional Outcomes
Bangkok	Bangkok Metropolitan Region	High-High	Low-Low
Nakhon Pathom	Bangkok Metropolitan Region	High-High	Low-Low
Nonthaburi	Bangkok Metropolitan Region	High-High	Low-Low
Pathum Thani	Bangkok Metropolitan Region	High-High	Low-Low
Samut Prakan	Bangkok Metropolitan Region	High-High	Low-Low
Samut Sakhon	Bangkok Metropolitan Region	High-High	Low-Low
Phra Nakhon Si Ayutthaya	Central	Not significant	Low-Low
Saraburi	Central	Not significant	Low-Low
Chachoengsao	East	High-High	Low-Low
Chanthaburi	East	Not significant	Low-Low
Chon Buri	East	Not significant	Low-Low
Nakhon Nayok	East	Not significant	Low-Low
Rayong	East	Not significant	Low-Low
Kamphaeng Phet	North	Low-Low	Not significant
Amnat Charoen	Northeast	Not significant	High-High
Bueng Kan	Northeast	Not significant	Low-High
Buri Ram	Northeast	Not significant	High-High
Kalasin	Northeast	Not significant	High-High
Khon Kaen	Northeast	Low-Low	High-High
Maha Sarakham	Northeast	Not significant	High-High
Mukdahan	Northeast	Not significant	High-High
Nakhon Phanom	Northeast	Not significant	High-High
Roi Et	Northeast	Low-Low	High-High
Sakon Nakhon	Northeast	Not significant	High-High
Si Sa Ket	Northeast	Low-Low	High-High
Surin	Northeast	Low-Low	High-High
Ubon Ratchathani	Northeast	Low-Low	High-High
Udon Thani	Northeast	Not significant	High-High
Yasothon	Northeast	Not significant	High-High
Ratchaburi	West	Not significant	Low-Low
Samut Songkhram	West	Not significant	Low-Low

Note: Provinces not listed are not statistically significant for either ranking.

Table A7. Provincial ranking by GPP per capita alone versus the economic prosperity TOPSIS ranking, 2022–2024.

Year	Spearman ρ	p -Value	N Provinces	Mean Rank Difference	Max Rank Difference
2022	0.710	<0.001	77	12.78	47
2023	0.712	<0.001	77	12.57	48
2024	0.753	<0.001	77	11.45	48

Note: Spearman rank correlation between the GPP per capita-only ranking and the six-indicator economic prosperity TOPSIS ranking, all 77 provinces.

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