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Original Research

Bridging Efficiency Gaps in ASEAN Agriculture: A Spatial SBM-DEA Approach

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ABSTRACT

Southeast Asia plays a strategic role in global rice production, yet agricultural performance across countries may be shaped not only by internal production conditions but also by spatial interaction mechanisms. This study investigates sustainable agricultural efficiency and spatial dependence across five major ASEAN rice-producing countries Indonesia, Thailand, Vietnam, Myanmar, and the Philippines over the period 2010–2023. Efficiency is evaluated using the Slacks-Based Measure Data Envelopment Analysis (SBM-DEA) framework, which accommodates multiple inputs, desirable outputs, and greenhouse gas emissions as an undesirable output. To capture spatial interdependencies, a distance-based spatial weight matrix is constructed using inverse distance weighting, followed by the estimation of Global Moran's I to assess spatial autocorrelation. The results indicate that technical efficiency levels are generally high across countries, suggesting relatively effective internal resource utilization, while spatial efficiency exhibits greater variability, implying that production performance cannot be fully interpreted without considering spatial effects. The Moran's I analysis reveals positive spatial autocorrelation, indicating that efficiency patterns display systematic spatial structures rather than purely independent national dynamics. These findings demonstrate that agricultural efficiency in regionally connected systems reflects both domestic production factors and geographically mediated influences. The study concludes that incorporating spatial dependence into efficiency evaluation provides a more comprehensive understanding of regional agricultural performance and offers a more appropriate analytical basis for policy formulation in interconnected agricultural systems.

1. INTRODUCTION

Global food security continues to represent a fundamental challenge amid population growth, climate change, and increasing pressure on natural resources. Agricultural systems play a central role in sustaining food availability and stability, particularly in regions where staple crops dominate dietary structures. In Southeast Asia, rice-producing ASEAN countries Indonesia, Thailand, Vietnam, Myanmar, and the Philippines occupy a strategically important position within regional and global food systems. Rice functions not only as a primary staple food but also as a critical component of rural livelihoods and national food security strategies. Despite strong production capacity, food security outcomes across the region remain complex, reflecting structural constraints, environmental pressures, and resource limitations (FAO 1996; FAO 2008).

Regional food security assessments emphasize that agriculture remains indispensable for hunger reduction and nutritional stability, yet the drivers of food insecurity are multifaceted. Persistent vulnerabilities may emerge even under conditions of aggregate food sufficiency, highlighting the importance of resource management, environmental sustainability, and institutional coordination ('Teng et al. 2021). These challenges have been further amplified by climate variability, water scarcity, demographic transitions, and systemic disruptions, reinforcing the need for analytical frameworks capable of capturing agricultural performance beyond conventional production metrics('Teng et al. 2021).

Food security is widely understood as a multidimensional construct encompassing availability, utilization, and stability. The FAO framework defines food security as a condition in which all individuals have consistent physical, social, and economic access to sufficient, safe, and nutritious food (FAO 1996), while subsequent refinements underscore stability as a critical dimension (FAO 2008). Within this perspective, agricultural efficiency becomes a key determinant of food system resilience, as the capacity to transform inputs into desirable outputs directly influences production sustainability. However, empirical findings on the relationship between agricultural efficiency and food security remain heterogeneous. While some studies identify positive associations between technical efficiency and food security outcomes, others suggest that efficiency improvements alone may not guarantee enhanced food security due to socio-economic and structural factors.

Methodologically, agricultural efficiency is frequently evaluated using Data Envelopment Analysis (DEA), a non-parametric approach suited to multi-input and multi-output production environments (Cooper et al. 2007). Conventional DEA models, however, typically assume independence among decision-making units and treat outputs as exclusively desirable. Such assumptions may be restrictive in sustainability-oriented analyses, where production processes often generate undesirable outcomes. The Slacks-Based Measure (SBM) DEA model offers a methodological advantage by explicitly incorporating slack adjustments and allowing the simultaneous treatment of desirable and undesirable outputs within a unified efficiency framework (Tone 2001). This modelling flexibility is particularly relevant in agricultural systems, where environmental externalities increasingly shape performance evaluation (Tsaples and Papathanasiou 2021)

Among environmental pressures, agricultural greenhouse gas (GHG) emissions have emerged as a critical concern. Agricultural activities constitute a substantial source of global emissions, reflecting the environmental costs associated with production processes. Recent evidence highlights that a significant share of global greenhouse gas emissions originates from agriculture and land-use dynamics, underscoring the necessity of incorporating environmental externalities into efficiency measurement (Mehmood et al. 2026). Ignoring undesirable outputs such as GHG emissions may therefore lead to biased efficiency estimates and incomplete sustainability assessments.

Beyond environmental considerations, agricultural systems are inherently embedded within spatial contexts. ASEAN countries share geographic proximity, agroecological similarities, and climatic interdependencies that may induce spatial dependence in production performance. Spatial analytical theory argues that geographically referenced observations are rarely independent, and neglecting spatial structures may bias statistical inference (Anselin 1988). Recent advances in spatial efficiency modelling demonstrate that incorporating spatial relationships into DEA frameworks can yield substantively different interpretations of efficiency relative to conventional approaches(Wang et al. 2021; Zhou et al. 2024). Empirical evidence further confirms that spatially augmented DEA models provide more informative evaluations of regional performance and environmental efficiency (Wen et al. 2016).

Despite growing recognition of spatial effects in efficiency analysis, empirical applications integrating sustainability-oriented DEA models with spatial dependence diagnostics remain limited in the ASEAN agricultural context. Existing studies often emphasize productivity or technical efficiency without explicitly accounting for undesirable outputs and spatial interdependencies. Addressing these gaps is essential for understanding how environmental constraints and geographic structures jointly shape agricultural performance.

This study evaluates sustainable agricultural efficiency and spatial dependence across Indonesia, Thailand, Vietnam, Myanmar, and the Philippines using an SBM-DEA framework combined with spatial diagnostics. Spatial relationships are modelled through an inverse distance weighting scheme, followed by Moran's I analysis to detect spatial autocorrelation and subsequent estimation of spatial efficiency. The findings indicate that incorporating undesirable outputs and spatial structures produces distinct efficiency patterns compared to conventional models, highlighting the analytical importance of spatially informed efficiency assessment in agricultural systems. These results contribute to methodological refinement while offering insights for sustainability-oriented policy design in ASEAN.

2. MATERIALS AND METHODS

This study examines sustainable agricultural efficiency and spatial spillover effects across five major ASEAN rice-producing countries, namely Indonesia, Thailand, Vietnam, Myanmar, and the Philippines, using annual panel data covering the period 2010–2023. The final dataset comprises 70 decision-making units (DMUs), representing country-year observations. The data were compiled from multiple authoritative and internationally recognized sources to ensure accuracy, consistency, and reproducibility. Primary data were obtained from the Food and Agriculture

Organization (FAO) database, complemented by information from the World Bank's World Development Indicators (WDI), as well as other official statistical repositories and publicly accessible government publications where necessary.

To ensure methodological rigor and analytical consistency, this study adopts an integrated quantitative framework. The subsequent section provides a detailed description of the analytical procedures, including the DEA model specification employed for efficiency measurement, the construction of the spatial weight matrix, and the estimation techniques applied in this study.

2.1 Slack-Based Measure Data Envelopment Analysis (SBM DEA)

Data Envelopment Analysis (DEA), a non-parametric technique, has been widely applied to evaluate the efficiency of countries and firms in resource utilization. However, conventional DEA models often do not adequately account for undesirable outputs, such as CO_2 emissions, which are essential when environmental performance is considered (Addis, 2025). To address this limitation, more recent methodological developments have introduced DEA frameworks that explicitly incorporate both desirable and undesirable outputs (Tone 2001).

In this study, efficiency is measured using the Slack-Based Measure Data Envelopment Analysis (SBM DEA) model proposed by Tone (2001). Unlike traditional radial DEA models, such as the CCR model of Charnes, Cooper, and Rhodes (1978), which assess efficiency through proportional input reduction or output expansion, the SBM DEA model adopts a non-radial approach by directly integrating input excesses and output shortfalls (slacks) into the objective function. This formulation enables non-proportional adjustments across variables and mitigates the potential bias associated with radial projections. The SBM DEA efficiency score for each decision-making unit (DMU) is defined as:

$$
\begin{aligned}
min \quad \rho = \left(1-(1/m)\Sigma_{i=1}^{m}(s_i^-/x_{i0})\right)/\left(1+(1/s)\Sigma_{r=1}^{s}(s_r^+/y_{r0})\right) \\
s.t. \quad x_0 = X\lambda + s^- \; s.t. \\
y_0 = Y\lambda - s^+ \\
\lambda \geq 0, s^- \geq 0, s^+ \geq 0 \qquad \ldots(1)
\end{aligned}
$$

where ρ denotes the SBM efficiency score, s_i^- and s_r^+ represent the input and output slack variables, respectively, and λ is the intensity vector defining the convex combination of reference DMUs. In the model, $x_0 \in \mathbb{R}^m$ and $y_0 \in \mathbb{R}^s$ denote the observed input and output vectors of the DMU under evaluation, respectively. The matrices $X \in \mathbb{R}^{m\times n}$ and $Y \in \mathbb{R}^{s\times n}$ represent the input and output matrices of all DMUs. The vector $\lambda \in \mathbb{R}^n$ defines the intensity weights, while $s^- \in \mathbb{R}^m$ and $s^+ \in \mathbb{R}^s$ capture input excesses and output shortfalls.

The efficiency score ρ is bounded within $0 < \rho \leq 1$, where a value of unity indicates that the DMU operates on the efficient frontier with no observable slacks. Values below unity imply inefficiency arising from excessive input usage, insufficient output production, or both. The SBM DEA model is employed due to its non-radial specification, which enables non-proportional adjustments and avoids projection bias inherent in radial DEA models (Tone 2001). The estimated efficiency scores are subsequently used for spatial dependence analysis.

2.2 Spatial Dependence and Spatial Weight Matrix

The conventional SBM-DEA framework assumes independence across decision-making units (DMUs). However, in agricultural systems, efficiency performance may exhibit spatial dependence due to geographic proximity, technology diffusion, similar agroecological conditions, and shared environmental constraints. Ignoring such spatial interactions may bias efficiency estimates, as observed outcomes can be partially influenced by neighboring units rather than purely internal factors. This perspective is consistent with spatial econometric theory, which emphasizes that spatially referenced observations are rarely independent ('Cliff and 'Ord 1981; Anselin 1988)

To explicitly capture spatial interactions, this study constructs a spatial weight matrix **W**, which defines the neighborhood structure and interaction intensity among countries. The spatial weight matrix is specified as an 5×5 matrix:

$$\begin{bmatrix} W_{11} & \cdots & W_{15} \\ \vdots & \ddots & \vdots \\ W_{51} & \cdots & W_{55} \end{bmatrix} \ldots(2)$$

where W_{kj}measures the spatial interaction between country $k$and country j. Diagonal elements $W_{kk}$are set to zero to exclude self-influence effects (Anselin, 1988).

Spatial weights are defined using inverse geographic distance:

$$W_{kj} = \begin{cases} \frac{1}{d_{kj}}, & k \neq j \\ 0, & k = j \end{cases} \quad \ldots(3)$$

where d_{kj}denotes the geographic distance between countries $k$and j. This formulation assumes that spatial influence decays with distance, a standard assumption in spatial analysis ('Cliff and 'Ord 1981; 'LeSage James' and 'Pace 2009)

To ensure comparability and numerical stability, the spatial weight matrix is row-standardized:

$$W_{kj}^{*} = \frac{W_{kj}}{\sum_j W_{kj}}, \sum_j W_{kj}^{*} = 1 \quad \ldots(4)$$

Row standardization ensures that spatial effects are interpreted as weighted averages of neighboring influences rather than absolute magnitudes, thereby avoiding scale distortions in spatial efficiency estimation. Descriptive statistics of the spatial weight matrix are reported to illustrate the connectivity structure and interaction intensity among countries.

Spatial dependence in efficiency scores is examined using spatial autocorrelation statistics. Spatial autocorrelation measures the degree to which the presence of similar attribute values in neighboring locations influences the spatial distribution of observations, thereby providing insight into clustering or dispersion patterns. Among the most widely applied global spatial autocorrelation measures are Moran's I.

Moran's I evaluates the correlation between attribute values at each location and those of neighboring locations defined through a spatial weight matrix. The statistic captures the covariance structure of spatially referenced observations and yields standardized values typically ranging between -1 and 1, where positive values indicate spatial clustering and negative values imply spatial dispersion.In contrast, Geary's c assesses the average squared differences between neighboring observations, providing an alternative representation of global spatial variation. Values of Geary's c below unity indicate positive spatial autocorrelation, values above unity indicate negative spatial autocorrelation, and values approaching unity suggest spatial randomness.

Despite the availability of alternative statistics, Moran's I is adopted in this study due to its higher sensitivity to global spatial patterns, interpretational clarity, and methodological consistency with spatial interaction models. Moran's I is extensively employed in empirical spatial analyses across disciplines, including regional science and spatial econometrics.

This study applies the Global Moran's I statistic, which provides a single summary measure of spatial autocorrelation across countries. Global Moran's I assesses whether efficiency scores are spatially random or systematically clustered within the defined spatial structure (Anselin 1995). The statistic is defined as:

$$I = \frac{N}{S_0} \cdot \frac{\sum_k \sum_j W_{kj}(E_k - \bar{E})(E_j - \bar{E})}{\sum_k (E_k - \bar{E})^2} \quad \ldots(5)$$

where $E_k$denotes the efficiency score of country k, $\bar{E}$represents the mean efficiency, $W_{kj}$is the row-standardized spatial weight matrix, N is the number of spatial units, and $S_0 = \sum_k \sum_j W_{kj}$.

Statistical inference is conducted using permutation-based significance tests, a standard approach for assessing the non-randomness of spatial patterns (Anselin, 1995).

To incorporate spatial interaction effects into ecological efficiency measurement, the conventional efficiency framework is extended by explicitly accounting for interdependencies among decision-making units (DMUs). In cross-country agricultural systems, environmental and production outcomes may not be solely determined by internal resource allocation but may also reflect spillover mechanisms arising from geographically proximate units. Ignoring such spatial interaction structures may therefore lead to biased efficiency estimates.

The spatial ecological efficiency specification utilized in this study follows the analytical framework proposed by Zhou et al. (Year), which explicitly incorporates spatial interaction effects into the DEA efficiency structure. This formulation enables efficiency measurement under spatial dependence by adjusting undesirable outputs to reflect neighboring influences, thereby providing a behaviorally consistent extension of conventional ecological efficiency analysis.

The initial spatial efficiency formulation is represented by Model (6), which integrates spatial spillover effects through the adjustment of undesirable outputs:

$$min\ \overline{\theta_0^{KW}} \quad \ldots(6)$$

$$\text{s.t.} \sum_{t\in W}\sum_{j=1}^{n}\lambda_j^t x_{ij}^t \le x_{i0}^{KW}, \quad i = 1,2,\ldots,m$$

$$\sum_{t\in W}\sum_{j=1}^{n}\lambda_j^t y_{rj}^t \ge y_{r0}^{KW}, \quad r = 1,2,\ldots,s$$

$$\sum_{t\in W}\sum_{j=1}^{n}\lambda_j^t b_{lj}^t \le \overline{\theta_0^{KW}}\left(b_{l0}^{KW} - \beta_j^{KW} b_{lj}^{KW}\right), \quad l = 1,2,\ldots,p$$

$$\sum_{t\in W}\sum_{j=1}^{n}\lambda_j^t = 1, \quad j = 1,2,\ldots,n$$

Model (6) assumes that undesirable outputs may be influenced by neighboring DMUs through the spatial interaction parameter β_j^{KW}, which captures spillover effects embedded within the spatial structure. As the estimation of Model (5) depends on the spatial interaction mechanism, the model is subsequently reformulated to obtain a tractable representation of spatial ecological efficiency.

Following the transformation procedure, Model (5) can be expressed as Model (7):

$$min\ \overline{\theta_0^{KW}} \quad \ldots(7)$$

$$\text{s.t.} \sum_{t\in W}\sum_{j=1}^{n}\lambda_j^t x_{ij}^t \le x_{i0}^{KW}, \quad i = 1,2,\ldots,m$$

$$\sum_{t\in W}\sum_{j=1}^{n}\lambda_j^t y_{rj}^t \ge y_{r0}^{KW}, \quad r = 1,2,\ldots,s$$

$$\sum_{t\in W}\sum_{j=1}^{n}\lambda_j^t b_{lj}^t \le \overline{\theta_0^{KW}}\ \delta_0^{KW}\ b_{l0}^{KW}, \quad l = 1,2,\ldots,p$$

$$\sum_{t\in W}\sum_{j=1}^{n}\lambda_j^t = 1, \quad j = 1,2,\dots,n$$

Model (7) measures the ecological efficiency of DMU 0after isolating the environmental effects attributable to neighboring units. In this formulation, spatial ecological efficiency reflects the efficiency position under a spatially adjusted production structure, where spillover effects are explicitly separated from internal production behavior.

The spatial efficiency score obtained from Model (7) represents the upper bound of attainable efficiency for a DMU when the full environmental impact of neighboring units is taken into account. Conceptually, this approach recognizes that observed inefficiency may arise not only from internal resource misallocation but also from external spatial mechanisms embedded within the interaction structure.

By separating internal and spatial effects, the model avoids conflating endogenous production inefficiency with exogenous spatial dependence. This distinction is particularly important in cross-country analyses, where geographic proximity and shared ecological conditions may generate interdependent efficiency outcomes.

Model (7) is reformulated to incorporate spatially neighboring DMUs into the efficiency frontier. The spatial DEA specification is presented in Model (8).

$$\min \widetilde{\theta_0^{KW}}/\delta_0^{KW} \dots(8)$$

$$\text{s.t.} \sum_{t\in W}\sum_{j=1}^{n}\lambda_j^t x_{ij}^t \le x_{i0}^{KW}, \quad i = 1,2,\dots,m$$

$$\sum_{t\in W}\sum_{j=1}^{n}\lambda_j^t y_{rj}^t \ge y_{r0}^{KW}, \quad r = 1,2,\dots,s$$

$$\sum_{t\in W}\sum_{j=1}^{n}\lambda_j^t b_{lj}^t \le \widetilde{\theta_0^{KW}}\, b_{l0}^{KW}, \quad l = 1,2,\dots,p$$

$$\sum_{t\in W}\sum_{j=1}^{n}\lambda_j^t = 1, \quad j = 1,2,\dots,n$$

Equation (8) represents a spatially restricted frontier, where benchmarking is constructed based on neighboring units. Based on this formulation, spatial efficiency can be decomposed into technical efficiency (TE) and spatial impact efficiency (IE), as expressed in Model (9).

$$SE = TE / IE \dots(9)$$

Technical efficiency (TE) is obtained from Model (1). Subsequently, the spatial impact efficiency (IE) is estimated using Model (10).

$$Min\delta_K W \dots(10)$$

$$\sum_{j=1}^{n}\mu_j x_{ij}^{KW} \le x_{i0}^{KW}, i = 1,2,\dots,m$$

$$\sum_{j=1}^{n}\mu_j y_{rj}^{KW} \ge y_{r0}^{KW}, r = 1,2,\dots,s$$

$$\sum_{j=1}^{n} \mu_j b_{lj}^{KW} \geq \delta_K W b_{l0}^{KW}, l = 1,2,\dots,p$$

$$\sum_{j=1}^{n} \mu_j = 1$$

$$\mu_j \leq SI_{j0}, j = 1,2,\dots,n$$

In Model (10), the optimal value δ_0^{KW}captures the maximum spatial influence of neighboring DMUs on the undesirable output of DMU₀. This value represents the spatial impact efficiency (IE). Furthermore, the ratio $\tilde{\theta}_0^{KW}/\delta_0^{KW}$in Model (8) reflects the ecological efficiency of DMU₀ after isolating the spatial spillover effect from surrounding units.

2.3 Variable Identification

Considering the research objectives and data availability, the variables were selected to represent agricultural production inputs and food security outcomes, as reflected by indicators derived from the Global Food Security Index (GFSI). The GFSI conceptualizes food security as a multidimensional outcome of the food system, encompassing availability, utilization, stability, and broader sustainability dimensions('Dragica and 'Marija n.d.; 'Guo and 'Islam 2025). This perspective allows food security to be interpreted as a systemic result of production and distribution processes rather than solely a consumption-based measure. Importantly, Chen et al. (2019) demonstrate that GFSI-related indicators can be operationalized within a Data Envelopment Analysis (DEA) framework, thereby supporting their use as output variables in efficiency evaluation. Accordingly, food security performance in this study is treated as a system-level outcome associated with agricultural production efficiency.

The input variables include fertilizer use, agricultural water use, agricultural energy use, agricultural labor, and agricultural land area, representing key production resources within the agricultural system. Outputs are defined in accordance with the conceptual structure of the GFSI. The availability dimension is proxied by Dietary Energy Supply (DES), utilization by Protein Supply, and stability by Food Supply Stability. These indicators are modeled as desirable outputs capturing the agricultural system's capacity to support food security outcomes. In addition, two undesirable outputs the number of undernourished people and agricultural greenhouse gas (GHG) emissions are incorporated to account for social and environmental externalities associated with agricultural production.

The study covers ASEAN countries for the period 2010–2023. All data were obtained from the Food and Agriculture Organization (FAO). Descriptive statistics are presented in Table 1.

Table 1: Descriptive Statistics of Input and Output Variables

Aspect	**Variable**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Input	Fertilizer Use	70	2,650,000,000	1,520,000,000	144,000,000	6,770,000,000
	Agricultural Water Use	70	20,200,000	169,000,000	94	1,420,000,000
	Agricultural Energy Use	70	4,590,000,000	2,800,000,000	82,600,000	9,910,000,000
	Agricultural Labor	70	58,400,000	37,800,000	22,100,000	141,000,000
	Agricultural Land Area	70	96,900,000	193,000,000	107,601	549,000,000
Output	DES (Availability)	70	27,816.14	1,387.44	24,110	30,860
	Protein Supply	70	781.27	115.15	606	995
	Food Supply Stability	70	281.43	116.65	0	460

Undesirable Output	Undernourished Population	70	148,000,000	138,000,000	5	588,000,000
	Agricultural GHG Emissions	70	1,870,000,000	2,350,000,000	112,000,000	9,570,000,000

3. RESULTS AND DISCUSSION

3.1. Technical Efficiency (TE) Scores from the SBM-DEA Model

The efficiency estimates derived from the SBM DEA model highlight distinct performance patterns across the five countries under investigation. Indonesia and Myanmar display the most consistent and stable efficiency trajectories, with scores predominantly equal to or very close to unity throughout the observation period. This stability indicates that both countries operate near the efficient frontier, reflecting their ability to utilize inputs effectively while maintaining desirable outputs and controlling undesirable outputs. The recurrent attainment of full efficiency further suggests that Indonesia and Myanmar frequently act as benchmark units, providing reference standards for other countries within the sample.

Conversely, Thailand and the Philippines exhibit relatively lower efficiency levels compared to their regional counterparts. For Thailand, the observed inefficiencies are systematically linked to slack values, particularly in protein supply, representing the utilization dimension of food security, and greenhouse gas (GHG) emissions, which constitute the undesirable output. The persistence of these slacks over time points to underlying structural challenges, implying that improvements are required in both nutritional performance and environmental management. The Philippines shows a similar tendency, with efficiency scores falling below unity in most years, indicating the presence of unresolved inefficiencies in resource utilization or output generation.

Vietnam demonstrates a moderately strong performance profile. Although the country does not achieve full efficiency in every year, its efficiency scores consistently remain close to unity. This finding implies that Vietnam's production system operates with relatively minor deviations from the efficient frontier, requiring only limited adjustments to reach full efficiency.The slack values associated with each country and period are presented in Table 2, offering a more detailed identification of inefficiency sources and potential directions for policy intervention.

Table 2 : Analysis of Slacks and Input-Output Inefficiency

No	DMU	DES	Protein Supply	Food Supply	Number of Undernourished	Agricultural GHG Emissions
1	Indonesia_2010	0	0	0	0	0
2	Indonesia_2011	0	0	0	0	0
3	Indonesia_2012	0	0	0	0	0
4	Indonesia_2013	0	0,793685	0	0,040829	0
5	Indonesia_2014	0	0	0	0	0
6	Indonesia_2015	0	0	0	0	0
7	Indonesia_2016	0	0	0	0	0
8	Indonesia_2017	0	0	0	0	0
9	Indonesia_2018	0	0	3,782789	0	3584,626434
10	Indonesia_2019	0	0	0	0	0
11	Indonesia_2020	0	0	0	0	0
12	Indonesia_2021	0	0	0	0	0
13	Indonesia_2022	0	0	0	0	0
14	Indonesia_2023	0	0	0	0	0
15	Thailand_2010	0	13,862154	21,984475	0	70236,11646

16	Thailand_2011	0	11,010325	22,476726	0	56595,60633
17	Thailand_2012	0	11,043552	4,666007	0	56173,38689
18	Thailand_2013	0	18,163024	0	0	59529,48206
19	Thailand_2014	0	19,011161	0	0	67739,011
20	Thailand_2015	0	19,189014	0	0	74928,68924
21	Thailand_2016	0	18,879528	0	0	70539,08139
22	Thailand_2017	0	18,470241	0	0	69492,37908
23	Thailand_2018	0	17,082843	0	0	73228,3664
24	Thailand_2019	0	18,207253	0	0	81994,78212
25	Thailand_2020	0	21,911474	0	0	76205,66752
26	Thailand_2021	0	15,178593	0	0	54362,63432
27	Thailand_2022	0	13,522145	0	0	29672,70013
28	Thailand_2023	0	20,729333	0	0,048553	27026,68516
29	Vietnam_2010	0	0	0	0	0
30	Vietnam_2011	0	0	0	0	0
31	Vietnam_2012	0	0	0	0	0
32	Vietnam_2013	0	0	0	0	0
33	Vietnam_2014	0	0	0	0	0
34	Vietnam_2015	0	0,461393	0	0	8882,498374
35	Vietnam_2016	0	0	9,083722	0	7734,152972
36	Vietnam_2017	0	0	14,390224	0	2517,291508
37	Vietnam_2018	24,101189	0	4,364724	0	0
38	Vietnam_2019	17,730331	0	2,869524	0	0
39	Vietnam_2020	0	0	0	0	0
40	Vietnam_2021	0	0	0	0	0
41	Vietnam_2022	32,89762	0	0	0	0
42	Vietnam_2023	0	0	0	0	0
43	Myanmar_2010	0	0	0	0	0
44	Myanmar_2011	0	0	0	0	0
45	Myanmar_2012	0	0	0	0	0
46	Myanmar_2013	0	0	0	0	0
47	Myanmar_2014	0	0	0	0	0
48	Myanmar_2015	0	0	0	0	0
49	Myanmar_2016	0	0	0	0	0
50	Myanmar_2017	0	0	0	0	0
51	Myanmar_2018	0	0	0	0	0
52	Myanmar_2019	0	0	0	0,245927	3086,333707
53	Myanmar_2020	0	0	0	0	0
54	Myanmar_2021	0	0	0	0	0
55	Myanmar_2022	0	0	0	0	0
56	Myanmar_2023	0	0	0	0	0
57	Philippines_2010	0	0	0	0	0
58	Philippines_2011	0	0	0	0	0
59	Philippines_2012	0	0	0	0	0
60	Philippines_2013	0	0	0	0	3317,730129
61	Philippines_2014	0	0	1,674625	0	1010,21799
62	Philippines_2015	0	0	0,933061	0	2656,510655
63	Philippines_2016	0	1,484369	0	0	5165,818568
64	Philippines_2017	0	0	0,194972	0	0
65	Philippines_2018	0	0	3,032568	0	0
66	Philippines_2019	0	0	14,510459	0	1544,540174

67	Philippines_2020	0	0	16,371611	0	3445,224153
68	Philippines_2021	0	0	1,585159	0	955,504773
69	Philippines_2022	0	0	0	0	0
70	Philippines_2023	0	0	0	0	0

In the output-oriented SBM-DEA framework, slack values represent output shortfalls and inefficiencies relative to the efficient frontier. Positive slack values indicate the extent to which desirable outputs should be increased and undesirable outputs should be reduced in order to achieve full efficiency. A slack value equal to zero implies that the DMU operates at the optimal level, whereas positive values reflect unrealized production potential. Therefore, higher slack values suggest greater opportunities for efficiency improvement through output expansion and environmental impact mitigation (Tone, 2001; Cooper et al., 2007).

3.2. Spatial Weight Matrix and Moran's I Analysis

The spatial interaction structure among the observed countries was defined using an inverse distance weighting (IDW) scheme as specified in Equation (3). This approach assumes that spatial influence diminishes with geographic distance, thereby capturing the distance–decay mechanism underlying inter-country relationships. The resulting spatial-weighting object, denoted as W_{invn}, was constructed and subsequently row-standardized to ensure numerical consistency and comparability across spatial units. The summary characteristics of the spatial weight matrix are presented in Table 3.

Table 3: Summary of spatial-weighting object W_invn

Matrix	Description
Dimensions	5x5
Stored as	5x5
Values	
Min	0
Min>0	.1295345
Mean	.2
Max	.4766829

Building upon the spatial configuration represented by the weight matrix, Global Moran's I was computed to assess the presence and direction of spatial autocorrelation in agricultural efficiency. The Moran's I statistic provides a quantitative measure of spatial dependence by evaluating the correspondence between observed values and their spatially weighted counterparts. The estimation results of Moran's I are reported in the subsequent section.

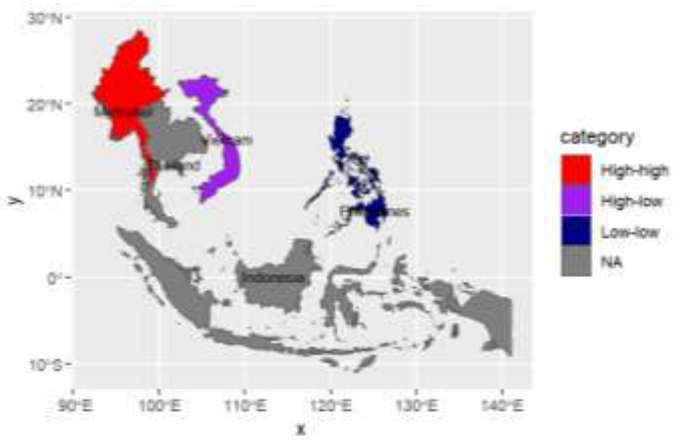

Fig 1. LISA Based Spatial Clustering

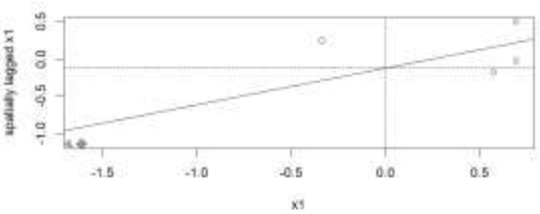

Fig 2. Moran's I Scatterplott

The Moran's scatterplot illustrates a positively sloped diagonal line, indicating a positive value of Moran's I. This pattern reflects the presence of positive spatial autocorrelation, meaning that regions with high values tend to be surrounded by neighboring regions with similarly high values, while regions with low values are generally adjacent to regions exhibiting low values. The relatively steep slope of the diagonal line further suggests a strong degree of spatial dependence among the observed regions.

The Local Indicators of Spatial Association (LISA) analysis provides a more detailed decomposition of this global spatial pattern by identifying localized clusters and spatial outliers. In particular, the High-High (HH) cluster represents regions with high values that are surrounded by neighbors also characterized by high values. This configuration typically indicates the existence of spatial concentration or agglomeration, where similar performance levels reinforce each other geographically.

The Low-Low (LL) cluster denotes regions with low values that are spatially proximate to other low-value regions. Such a pattern signifies the formation of spatial pockets of relatively weak performance, suggesting that structural constraints or unfavorable conditions may be shared across neighboring regions.

In contrast, the Low-High (LH) category captures spatial outliers, referring to regions with low values that are surrounded by high-value neighbors. This configuration implies spatial disparity, where a region's performance deviates markedly from its surrounding context. The presence of LH patterns may indicate localized inefficiencies, transitional dynamics, or region-specific constraints that prevent convergence with neighboring high-performing areas.

3.3 Spatial Efficiency Analysis

Table 6 presents the comparison between technical efficiency (TE) and spatial efficiency (SE) for the five ASEAN countries during 2010–2023. The results indicate that most DMUs exhibit consistently high TE scores, with values close to unity in almost all periods. This finding suggests that, from a conventional DEA perspective, agricultural production in the selected countries operates near the efficiency frontier.

However, the spatial efficiency scores show substantially lower and more volatile values compared to TE. In many cases, DMUs with high TE values record relatively low SE scores, indicating that strong internal production performance is not necessarily accompanied by favorable spatial interactions. This discrepancy implies that regional spillover effects, neighboring conditions, and spatial externalities play a significant role in shaping overall efficiency.

Table 6: Comparison of TE and SE

DMU	TE	SE	DMU	TE	SE
Indonesia_2010	0.9918	0.5091	**Myanmar_2020**	1.0000	0.7327
Indonesia_2011	0.9959	0.5347	**Myanmar_2021**	1.0000	0.7296
Indonesia_2012	0.9609	0.5087	**Myanmar_2022**	1.0000	0.8528
Indonesia_2013	0.9986	0.0297	**Myanmar_2023**	1.0000	0.6012
Indonesia_2014	0.9959	0.5000	**Philippina_2010**	0.9508	0.4916
Indonesia_2015	0.9609	0.5312	**Philippina_2011**	0.9347	0.2696
Indonesia_2016	0.9986	0.7998	**Philippina_2012**	0.9493	0.4830
Indonesia_2017	1.0000	0.5765	**Philippina_2013**	1.0000	0.3188
Indonesia_2018	0.9871	0.6000	**Philippina_2014**	0.9214	0.2361
Indonesia_2019	0.9856	0.9658	**Philippina_2015**	0.9235	0.5165
Indonesia_2020	0.9810	0.5172	**Philippina_2016**	0.9508	0.8143
Indonesia_2021	0.9784	0.5193	**Philippina_2017**	0.9347	0.3218

Indonesia_2022	0.9918	0.5250	**Philippina_2018**	0.9493	0.6225
Indonesia_2023	0.9913	0.2258	**Philippina_2019**	0.9565	0.9736
Myanmar_2010	1.0000	0.7188	**Philippina_2020**	0.9559	0.4957
Myanmar_2011	1.0000	0.6284	**Philippina_2021**	0.9701	0.4929
Myanmar_2012	1.0000	0.7149	**Philippina_2022**	1.0000	0.8270
Myanmar_2013	1.0000	0.1548	**Philippina_2023**	1.0000	0.4978
Myanmar_2014	1.0000	0.5992	**Thailand_2010**	0.9649	0.2599
Myanmar_2015	1.0000	0.7384	**Thailand_2011**	0.9698	0.1750
Myanmar_2016	1.0000	0.9669	**Thailand_2012**	0.9656	0.2554
Myanmar_2017	1.0000	0.3764	**Thailand_2013**	0.9620	0.1698
Myanmar_2018	1.0000	0.5497	**Thailand_2014**	0.9649	0.1366
Myanmar_2019	0.9927	0.9695	**Thailand_2015**	0.9698	0.2884
Thailand_2017	0.9620	0.4871	**Thailand_2017**	0.9620	0.4871
Thailand_2018	0.9670	0.6176	**Thailand_2018**	0.9670	0.6176
Thailand_2019	0.9793	0.9710	**Thailand_2019**	0.9793	0.9710
Thailand_2020	0.9957	0.2587	**Thailand_2020**	0.9957	0.2587
Thailand_2021	0.9859	0.2602	**Thailand_2021**	0.9859	0.2602
Thailand_2022	0.9825	0.5058	**Thailand_2022**	0.9825	0.5058
Thailand_2023	0.9911	0.1324	**Thailand_2023**	0.9911	0.1324
Vietnam_2010	1.0000	0.7717	**Vietnam_2017**	0.9661	0.2036
Vietnam_2011	0.9739	0.6041	**Vietnam_2018**	0.9573	0.4282
Vietnam_2012	1.0000	0.7658	**Vietnam_2019**	0.9502	0.9782
Vietnam_2013	0.9739	0.1863	**Vietnam_2020**	1.0000	0.7826
Vietnam_2014	1.0000	0.5991	**Vietnam_2021**	1.0000	0.7814
Vietnam_2015	0.9739	0.7618	**Vietnam_2022**	0.9955	0.5722
Vietnam_2016	0.9620	0.7731	**Vietnam_2023**	1.0000	0.5756

For Indonesia, although TE remains consistently high throughout the study period, SE fluctuates considerably and declines sharply in certain years, such as 2013 and 2023. This suggests that Indonesia's production efficiency is primarily driven by internal factors, while spatial linkages with neighboring countries are relatively weak in some periods.

Myanmar demonstrates near-perfect TE scores across most years; nevertheless, its SE values vary markedly, particularly in 2013 and 2017. This pattern indicates that despite operating on the efficiency frontier, Myanmar does not always benefit from positive regional spillovers. The Philippines and Thailand display relatively lower and more unstable SE values in the early years, followed by noticeable improvements around 2016-2019. These improvements may reflect enhanced regional integration, technology diffusion, and policy coordination. Similarly, Vietnam shows high TE performance but experiences substantial variations in SE, with particularly strong spatial effects observed in 2019-2021.

Overall, the comparison reveals that high technical efficiency does not automatically translate into high spatial efficiency. While TE reflects internal managerial and technological performance, SE captures the influence of geographical proximity and interregional interactions. The observed gaps between TE and SE suggest that efficiency enhancement strategies should not only focus on improving internal production processes but also emphasize regional cooperation, infrastructure connectivity, and knowledge spillovers.

4. CONCLUSIONS

This study shows that agricultural efficiency exhibits different characteristics once spatial interdependencies are incorporated into the analytical framework. While conventional SBM-DEA results indicate that countries generally operate near the efficiency frontier, spatial efficiency estimates reveal that internal production performance alone does not fully capture observed efficiency dynamics. The divergence between technical and spatial efficiency highlights the role of spatial dependence and geographically mediated effects in shaping efficiency outcomes. The findings suggest that efficiency behavior in regionally connected systems reflects both domestic production factors and spatial interaction mechanisms. The analysis is conducted within a defined empirical scope and a distance-based spatial structure, consistent with established spatial modeling practices. Future research may extend this framework by exploring alternative spatial specifications and broader regional contexts.

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