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The driver of global agricultural value chains: Evidence from 6 ASEAN Countries

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Abstract. This study investigates the drivers of global agricultural value chain (GAVC) participation in six ASEAN countries: Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam. Employing panel geographically weighted regression, the paper analyzes the spatial heterogeneity of factors influencing global agricultural value chain participation. Our findings reveal significant variations in the impact of tariffs, FDI, agricultural land area, inland waters, and trade balance across countries. Tariffs emerge as a crucial factor in enhancing competitiveness in Indonesia, Singapore, and Thailand, aligning with trade theory. FDI positively influences Malaysia's global agricultural value chain participation, emphasizing attracting foreign investment. Agricultural land area plays a pivotal role in Indonesia and Thailand, highlighting the significance of resource endowments. Inland waters contribute significantly to agriculture in the Philippines, while their impact in Indonesia suggests potential inefficiencies in water management. Trade balance in food products positively affects global agricultural value chain involvement in Thailand and Vietnam. These findings underscore the need for tailored policies to address the unique characteristics of each ASEAN country. Future research should explore the long-term implications of these factors and consider broader socio-economic and environmental contexts.

Keywords: Agriculture; Agricultural Clusters; Firm Scales; PCA

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1. Introduction

The agricultural sector has significantly transformed from mainly domestic to highly interconnected across countries since the Uruguay Round Agreement in 1994 [1]. The process of producing and trading food has evolved substantially in recent years. Instead of focusing solely on domestic production and sales, countries now collaborate in a global food system, referred to as a global value chain. Some countries specialize in food production, others in food processing, and others in selling food products. This integration has been propelled by recent technological advancements, trade liberalization, and shifts in consumer preferences [2].

In recent years, the literature on sectoral GVCs has grown exponentially, focusing on manufacturing sectors, and the agricultural domain has received relatively less attention. However, agriculture is essential in recent development issues such as healthy food security. According to a recent update from [3], the number of people experiencing hunger worldwide increased to an estimated 713 to 757 million between 2022 and 2023. Recent data indicates that over a third of the world's population could not afford a nutritious diet in 2022. Unfortunately, it appears that the global community will not meet any of the established nutrition goals by the year 2030.

In that context, understanding the drivers of global agricultural value chains is increasingly critical for developing effective policies to ensure food security and promote sustainable agricultural development. As populations have expanded and dietary preferences have diversified, nations have increasingly depended on imports to fulfil their domestic food requirements [4]. More importantly, climate-related events have caused widespread ecosystem damage and threaten food security [5]. Thus, global agricultural value chains offer opportunities for countries to access a broader range of farm products, improve food quality, and reduce food costs [6]. However, the complex interdependencies within these chains also expose countries to risks such as price volatility, supply chain disruptions, and trade barriers. By investigating these drivers, policymakers and stakeholders can develop more effective strategies to ensure food availability, accessibility, affordability, and nutritional quality for all.

Existing studies have primarily explored the impact of global agricultural value chain participation on food prices and economic development [7,8]. While these studies provide valuable insights, a deeper understanding of the drivers of global agricultural value chains is essential for formulating effective policies that promote food security and sustainable agriculture. Studying individual countries within specific regions will provide a better understanding of the drivers of the global agricultural value chain [9]. This study aims to identify and quantify the drivers of global agricultural value chain participation in the ASEAN region to address this gap. All six ASEAN countries consistently maintained a higher share of agricultural exports than the global average throughout the period. Indonesia and Thailand demonstrated the highest shares, indicating an important country as a top exporter country

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for agricultural products [see Table 1). Thus, ASEAN plays an important role in tackling global hunger issues.

This study seeks to contribute to the drivers of global agricultural value chain involvement of six ASEAN countries – Indonesia, Singapore, Malaysia, Thailand, Philippines, and Vietnam. The ASEAN region offers a unique context for this research. ASEAN remains a global agricultural powerhouse, producing significant quantities of staple crops [10]. As a result, both domestic consumption and exports are expected to rise in 2024. ASEAN is a big market for food demand due to the population is nearly 700 million people. Many of these populations belong to a growing middle class, which prefers higher-quality foods, including organic and processed options [11]. In terms of economic development, agricultural structure, and policy environment, the region has experienced rapid economic growth and integration.

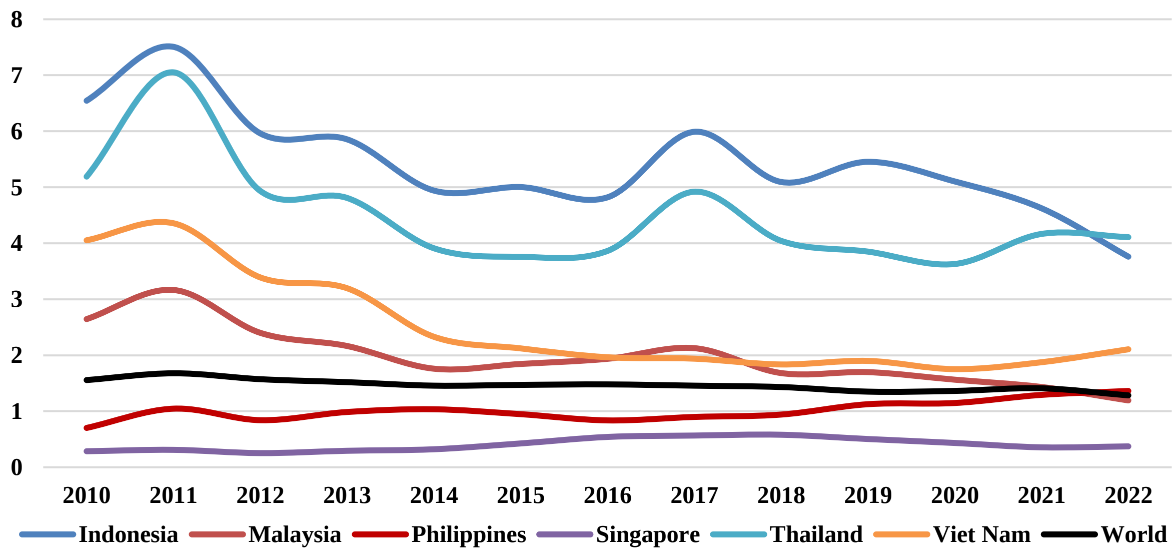

Figure 1. Agricultural raw materials exports (% of merchandise exports) [12].

Building upon existing research on the global agricultural value chain, this study contributes to the literature by employing geographically weighted panel regressions to account for spatial heterogeneity. First, it comprehensively analyzes the determinants of global agricultural value chain participation in the ASEAN region. The region that has received less attention in GVC research than other region. Second, it employs geographically weighted panel regressions to capture spatial heterogeneity, local relationships, and spatial autocorrelation. Third, the findings offer valuable insights for policymakers in the ASEAN region seeking to enhance their countries' participation in the global agricultural value chain.

Understanding how the factors influencing global agricultural value chain participation differ across countries is crucial for highlighting the urgency of this study. ASEAN countries exhibit significant economic, geographic, and policy variations, which shape their distinct roles within the agricultural value chain. For instance, resource-rich nations like Indonesia and Thailand

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may rely heavily on agricultural land endowments. At the same time, highly urbanized and trade-oriented countries like Singapore depend on tariff reductions and trade facilitation to remain competitive. Similarly, the role of foreign direct investment (FDI) may be more pronounced in countries like Malaysia, where attracting international capital has been central to economic development. At the same time, other nations might benefit more from improving water management or enhancing trade balances in food products. These differences underscore the need for a tailored approach to policymaking, as the same strategies may not yield uniform results across countries. By addressing this spatial heterogeneity, the study emphasizes the importance of identifying country-specific determinants to develop more effective, regionally nuanced policies to enhance GAVC participation and overall competitiveness in the global market.

Furthermore, the study's insights into the role of trade policies, FDI, land use, inland water, and trade balances in shaping GVC participation can help ASEAN countries better navigate the challenges and opportunities of global agricultural markets. However, the study focuses on economic policy and resource endowments, excluding socio-political influences and global trends like climate change. This exclusion is motivated by isolating the economic policy and resource endowment determinants directly influencing participation in global agricultural value chains.

Our findings indicate the spatial heterogeneity in the drivers of the global agricultural value chain across ASEAN countries. While some factors, such as FDI and agricultural land area, have consistent impacts, others, like tariffs and inland waters, exhibit varying effects depending on the specific country context.

The emerging topic of global agricultural value chains has attracted significant scholarly attention in recent years. Researchers have explored various topics, from the underlying drivers of GVC formation and evolution to their impacts on various economic, social, and environmental dimensions. A primary focus has been on understanding the factors that influence the participation of countries and regions in GVCs, including trade policies [4], technological advancements [6], institutional frameworks, and resource endowments [13].

A growing body of literature explores the drivers influencing countries' participation in global agricultural value chains. This review synthesizes key findings from existing research, focusing on trade policies [4], land reform [14], resource endowments [2], and infrastructure [13] as key drivers.

One significant driver of GVC participation is trade policy, which fundamentally shapes a country's ability to engage in international trade. The tariff levels countries encounter limits their ability to trade commodities for final goods, as per the conventional structure, and their involvement in both forward and backward worldwide value chains (GVCs) [4]. Furthermore, the findings indicate a "chain effect" resulting from the exporter's import tariffs; in particular, border barriers may reduce the local value-added employed by trading partners that

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ultimately revert to the exporter. Therefore, reducing trade barriers can enhance global connectivity and improve the overall efficiency of agricultural value chains.

Land reform substantially enhanced agriculture production and yields [14] that important for AGVCs [2]. Specifically, the redistribution of public land markedly enhanced rice production and yields; conversely, land-to-the-tillers unexpectedly did not influence either. The differential effects can be attributed to two factors: first, the public land's redistribution of sugar company land alleviated constraints on crop selection, enabling farmers to cultivate a second rice crop. Second, in contrast to the public land redistribution, land-to-the-tiller redistribution reduced median farm sizes, resulting in economically unviable farms due to their small scale. This disparity is partly because these policies led to smaller, economically unviable farm sizes, highlighting the importance of considering optimal farm scale in land reform initiatives for them to be effective.

The third critical driver is resource endowment and infrastructure, as noted by [13]. Effective infrastructure facilitates the efficient movement of goods and services, enabling better integration into global markets. With strong infrastructural support, agricultural products can reach international markets more effectively, enhancing a country's global agricultural value chain participation. Similarly, resource endowment—encompassing natural, human, and technological resources—plays a substantial role in determining a country's capacity to engage in and benefit from global agricultural markets.

In summary, the global agricultural value chain drivers are interconnected and complex, involving trade policy, land reform, resource endowment, and infrastructure. Policymakers must address these factors holistically to enhance participation in the global agricultural value chain. By doing so, they can craft strategies that improve agricultural productivity and global trade participation and ensure sustainable and equitable growth. This comprehensive approach is crucial for leveraging the full potential of global agricultural value chains in today's interconnected world.

The current literature offers substantial insights into global agricultural value chain drivers, yet gaps remain in understanding these dynamics within the ASEAN context. Most studies focus on individual country or global perspectives, with insufficient attention to regional specifics such as ASEAN's unique trade policies, diverse resource endowments, and varied agriculture infrastructural developments. The critical review indicates that while ASEAN countries participate in GVCs, the role of regional trade agreements, political stability, and local institutional frameworks requires deeper exploration. Investigating these factors is crucial to tailoring effective policies that enhance ASEAN's integration into the global agricultural economy, promoting sustainable development across member states.

The remainder of this paper is structured as follows. In Section Two, the focus is on the data and methodology used in the study. This section details the data sources, followed by a thorough description of how the variables were constructed. Additionally, this section outlines

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the econometric model employed, which utilizes panel geographically weighted regression (GWR) to capture the spatial heterogeneity of the factors influencing GAVC participation. In Section Three, the paper presents and discusses the empirical results. This section includes a detailed analysis of the findings and how they relate to existing literature on global value chains, agriculture, and trade. The results are discussed in the context of relevant theoretical frameworks, and comparisons are drawn with prior studies to highlight similarities and differences. Finally, Section Four provides the conclusion, offering key policy implications and limitations and suggests directions for future research based on the findings.

2. Methods

This study draws upon diverse data sources to address the research objectives. By leveraging these data, we can comprehensively explore the relevant variables and methodologies required for a thorough investigation. This section provides a detailed overview of the datasets utilized and the specific methods employed in this research.

2.1. Data

The study uses various variables to investigate the drivers of the global agricultural value chain forward participation in Southeast Asia. This study proposes a theoretical and empirical framework that incorporates the following independent variables: tariff, foreign direct investment (FDI), agricultural land area, inland waters, and trade balance in food (see Table 1). We transformed these variables into logarithm natural.

Table 1. Variable description.

Variable	Measurement	Description	Source
GAVCs	Million USD	Global agricultural value chain forward participation absolute where the ratio of domestic value-added is higher than that of partner countries because it is more dominated by domestic products than by imports.	WITS
Tariff	%	AHS Weighted Average: This is the average tariff rate weighted by the value of imports. It gives a more accurate picture of the overall tariff burden.	World Bank
FDI	Million USD	Inward.	UNCTAD
Agri Land Area	Ha	Agriculture Land Area	FAO
Inland waters	Ha	Any area of water not categorised as “sea” – for example, canals, tidal and non-tidal rivers, lakes, and some estuarial waters (an arm of sea that extends inland to meet the mouth of a river).	FAO
Trade balance food	Million USD	International trade of food.	UNCTAD
Latitude-Longitude of the capital	Degrees (°) and minutes (′)	Latitude-Longitude of the capital.	Google Map

Among these factors, tariffs emerge as a critical policy instrument that considerably impacts domestic industries' competitiveness and participation in global value chains. Research by [4,15,16] emphasizes that trade policies crucially shape GVC participation and the distribution

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of benefits. Thus, understanding the role of tariffs provides insight into how Southeast Asian countries can optimize their trade policies to enhance market access and international competitiveness.

Furthermore, foreign direct investment (FDI) is another crucial determinant of global agricultural value chain involvement by promoting technology transfer, expanding market access, and fostering job creation. Pioneering studies by [17,18] highlight the significant impact of FDI on economic development and industrialization processes. FDI serves as a conduit for innovation and capacity building, essential for agriculture sectors looking to integrate more deeply into global markets and move up the value chain.

Additionally, the availability of agricultural land is a fundamental factor influencing agricultural production capabilities and trade. Countries with substantial agricultural land resources often hold a comparative advantage in agriculture, facilitating their effective participation in the global agricultural value chain [19–21]. Land endowments significantly shape agricultural trade patterns, underscoring the importance of geographic and environmental factors in determining economic outcomes.

Moreover, access to water resources is indispensable for sustained agricultural production and significantly affects the competitiveness of agricultural sectors. Comprehensive studies by [22,23] stress the critical nature of water management policies and infrastructure in supporting sustainable agriculture. Effective management ensures that agricultural practices are both viable and resilient, thus enhancing a region's capacity to provide valuable contributions to GVCs.

Finally, the trade balance in food products, reflecting net agricultural exports or imports, is a crucial indicator of a country's agricultural competitiveness. A favorable trade balance signals a robust ability to engage in GVCs, driven by strategic advantages in production and distribution. Research by [4,24] explores the numerous factors, such as trade policies, exchange rates, and productivity levels, that influence agricultural exports and imports, providing a multifaceted understanding of global trade dynamics.

By integrating these independent variables into a geographically weighted regression analysis, this study offers in-depth insights into the complex interactions affecting agricultural GVC participation in ASEAN countries. The application of geographically weighted panel regressions facilitates the identification of spatial variations within these relationships, delivering a nuanced understanding of the unique drivers shaping GVC involvement in each country. This methodological approach enhances our theoretical understanding and supports the formulation of targeted policies that effectively address each regional context's needs and opportunities.

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Table 2. Descriptive statistic.

Variable	Min	1st Qu.	Median	Mean	3rd Qu.	Max
Global agricultural value chain	9.394	725.223	1698.977	2043.019	3381.358	5422.848
Tariff	0.6485	4.1426	6.9126	10.8676	17.7316	35.1211
FDI	1070	6941	9278	16299	15624	85369
Agri Land Area	0.66	7601.73	10600	15141.62	22031	43941
Inland waters	1000	183000	224000	978166	1784600	3930100
Trade balance food	-3968	-1673	8663	7684	15119	21765

As Table 2 shows, starting with the global agricultural value chain suggests a right-skewed distribution, indicating the presence of some high-value outliers within the dataset. The mean tariff rate suggests a right-skewed distribution. This skewness indicates that while most tariff rates are relatively low, a few countries apply significantly higher tariffs, impacting the average. The Foreign Direct Investment (FDI) statistics exhibit significant variability. The high maximum and mean relative to the median point towards a distribution skewed to the right, masked by substantial investments in a few countries or regions.

Agricultural Land Area indicates significant land holdings for many countries, and few countries possess much larger areas, skewing the average upwards. Inland waters data demonstrate a significant variability in water resources across countries. The right-skewed distribution highlights the diverse availability of water resources, critical for agricultural and economic activities. Finally, the Trade Balance for Food variable suggests some countries have significant food trade deficits while indicating substantial surpluses in others. The median trade balance suggests a relatively balanced distribution, with some countries maintaining large surpluses that pull the average upwards.

These descriptive statistics highlight the diverse economic landscapes across countries involved in the global agricultural value chain, with notable skewness in distributions indicating varying levels of influence by a few high or low values within each dataset. Understanding these characteristics is crucial for policymakers and stakeholders aiming to improve engagement in global agricultural markets and address economic disparities.

2.2. Geographically weighted panel regressions

The paper utilizes geographically weighted panel regressions to demonstrate various spatial coefficients (spatial non-stationarity) with panel data [25]. The GWPR model uses spatial data with a latitude and longitude coordinate point approach, thus allowing model parameters to vary at each location. The general panel regressions model is as follows:

$$GAVC_{it}= \beta0_i+ \beta1_i tariff_{it}+ \beta2_i fdi_{it}+ \beta3_i agri\_land_{it}+ \beta4_i Inland\_Water_{it}+ \beta5_i Trade\_Balance_{it}+ \varepsilon_{it}$$

This study employs a geographically weighted panel regressions approach incorporating a kernel function to investigate the drivers of global agricultural value chain forward participation in Southeast Asia. The geographically weighted panel regressions allow for estimating spatially varying relationships between the dependent variable (global agricultural

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value chain forward participation) and the independent variables (tariff, FDI, agricultural land area, inland waters, and trade balance in food). The regression coefficients ($\beta1_i$, $\beta2_i$, $\beta3_i$, $\beta4_i$, $\beta5_i$) are allowed to vary across space, capturing local patterns and heterogeneities in the relationships between variables. The equation for the GWPR model is represented as follows:

$$y(u_{it},v_{it}) = \beta_0(u_{it},v_{it}) + \sum_{k=1}^{x} \beta_k(u_{it},v_{it})\, x_k(u_{it},v_{it}) + \varepsilon(u_{it},v_{it})$$

The transformation from a traditional panel regression model into a geographically weighted panel regression introduces spatial variability into the analysis, enabling the regression coefficients to vary across geographic locations. In the standard panel regression framework, a single set of coefficients is estimated for the entire dataset, assuming that the relationships between the dependent and independent variables are constant across all countries. However, the GWPR model relaxes this assumption by incorporating geographic coordinates (u_{it},v_{it}), which represent the spatial location of each country at time (t). This spatial dimension allows the regression coefficients $\beta_k(u_{it},v_{it})$ to vary depending on the specific location of each observation [25].

Thus, in the GWPR model, the impact of independent variables—such as tariffs, foreign direct investment (FDI), agricultural land area, inland water resources, and trade balance—can differ from one country to another, reflecting the spatial heterogeneity of economic and geographic conditions. For instance, the effect of tariffs on global agricultural value chain participation in Indonesia may differ from that in Thailand due to their unique economic contexts and geographical characteristics. The error term $\varepsilon(u_{it},v_{it})$ also varies spatially, capturing residuals specific to each location. This transformation enables a more nuanced understanding of how economic drivers of GAVC participation operate differently across ASEAN countries, providing insights into region-specific policies that can address each country's unique challenges and opportunities. GWPR offers a powerful tool for analyzing spatially varying relationships in the context of GAVC participation by allowing coefficients to be geographically weighted.

The first step involves constructing a spatial weight matrix using a kernel function. This matrix defines the spatial relationships between observations and determines the extent to which neighbouring data points influence the local regression estimates. Common kernel functions include Gaussian, bisquare, and uniform [25]. The choice of kernel function depends on the desired spatial weighting pattern and the specific research context.

Once the kernel function is selected, the kernel bandwidth must be determined. The bandwidth controls the extent of the spatial neighbourhood considered in the local regression. A larger bandwidth includes a wider range of observations, while a smaller bandwidth focuses on a more localized neighbourhood. Various methods, such as cross-validation or likelihood-based approaches, can select the optimal kernel bandwidth [26].

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Next, the geographically weighted panel regressions model is estimated using an iterative process. In each iteration, the regression coefficients are calculated for a specific location, considering the weighted influence of neighbouring observations as defined by the spatial weight matrix. The local regression estimates are then used to update the spatial weights, and the process is repeated until convergence is achieved [27].

The geographically weighted panel regression results provide spatially varying regression coefficients for each independent variable. By mapping these coefficients, it is possible to identify regions with significantly different relationships between the global agricultural value chain forward participation and its drivers. This can help to uncover local patterns and heterogeneities that may not be apparent in a traditional global regression analysis.

3. Result and discussion

The Variance Inflation Factor (VIF) for Tariff, FDI, Agricultural Land Area, Inland Waters, and Trade Balance Food aims to detect multicollinearity. VIF values above 5 or 10, conservatively, raise multicollinearity concerns [28]. The VIF results across variables suggest multicollinearity cannot destabilize the regression model [29]. Multicollinearity is not a threat because each variable is independent. Thus, the model's outputs are interpretable and reliable as seen in Table 3.

Table 3. Variance inflation factor.

Variable	Variance Inflation Factor
Tariff	3.199
FDI	1.232
Agri Land Area	4.312
Inland waters	4.615
Trade balance food	4.381

The kernel function is an essential element of geographically weighted panel regressions, as it dictates the weight allocated to each sample according to its proximity to the focal position. The kernel function decision can profoundly influence the geographically weighted panel regressions estimation outcomes [30]. Based on the provided AIC (Akaike Information Criterion) and R-squared values, the Fixed Exponential kernel function appears to be the most suitable for this analysis. The AIC evaluates the model's overall fit while imposing a penalty for the quantity of parameters. A lower AIC value indicates a better-fitting model [31]. Among the options, the Fixed Exponential kernel has the lowest AIC, suggesting it best balances model fit and complexity. R-squared measures the proportion of variance explained by the model. A higher R-squared indicates a better fit. The Fixed Exponential kernel also has the highest R-squared value, indicating it explains a more significant portion of the variation in the dependent variable.

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Table 4. Kernel function.

AIC	R2	Model
61.827	0.645	Adaptive Bisquare
-14.875	0.309	Adaptive Gaussian
-23.291	0.375	Adaptive Exponential
-37.474	0.491	Fixed Bisquare
-80.844	0.719	Fixed Gaussian
-95.579	0.767	Fixed Exponential

While the Adaptive kernels (Bisquare, Gaussian, and Exponential) also perform reasonably well, the Fixed Exponential kernel consistently outperforms them in terms of AIC and R-squared (see Table 4). This suggests that a fixed bandwidth used in the Fixed Exponential kernel is more appropriate for capturing this dataset's spatial relationships. The choice of kernel function can affect the estimated coefficients and their spatial patterns [32]. Therefore, it's essential to carefully consider the properties of different kernels and their suitability for the specific research question and dataset. The Fixed Exponential kernel seems the most appropriate choice based on the model fit and explanatory power.

The geographically weighted panel regression analysis results reveal the diverse drivers influencing the global agricultural value chain across Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam. Each of these countries exhibits unique interactions between the variables of tariff, foreign direct investment (FDI), agricultural land area, inland waters, and trade balance food, reflecting varied economic strategies and resource management approaches. Tariffs, for instance, show a significant impact in Indonesia, Singapore, and notably in Thailand. In Indonesia, the positive coefficient of 0.346* suggests that tariffs may protect and promote local agricultural industries by shielding them from international competition, a strategy backed by literature emphasizing its role in fostering domestic agricultural sectors [16]. The tariff's significance in Singapore (0.161*) supports its function as a regulatory tool in a country heavily reliant on imports and re-exports, aligning with the strategic adaptation in global trade frameworks documented by [15]. Thailand's substantial coefficient of 0.520** underscores tariffs as a critical mechanism in its agricultural export strategy, reflecting the country's policy priorities to strengthen its competitive edge in the ASEAN agricultural sector (see Table 5).

Table 5. Geographically weighted regression results.

Variable	Indonesia	Malaysia	Philippines	Singapore	Thailand	Vietnam
Tariff	0.346* (0.231)	0.014 (0.047)	0.002 (0.160)	0.161* (0.055)	0.520** (0.170)	0.199 (0.199)
FDI	0.079 (0.088)	0.149* (0.059)	0.027 (0.092)	0.043 (0.057)	-0.056 (0.076)	-0.083 (0.359)
Agri Land Area	6.219** (2.388)	-1.273* (0.554)	-1.090 (2.955)	1.333* (0.590)	6.837** (1.901)	3.433** (1.255)
Inland waters	-3.760** (1.677)	1.141 (0.826)	18.473** (5.344)	-0.396 (0.844)	-0.209 (5.139)	1.373 (4.262)

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Variable	Indonesia	Malaysia	Philippines	Singapore	Thailand	Vietnam
Trade balance food	0.113* (0.067)	-0.006 (0.020)	0.106 (0.082)	-0.020 (0.019)	1.406** (0.279)	2.291** (0.501)
R-square	0.868	0.537	0.502	0.638	0.937	0.948

*** (p-value < 0.001), ** (p-value < 0.01), * (p-value < 0.05), .(p-value < 0.1).

FDI presents a positive influence in Malaysia (0.149*), suggesting the country's effective utilization of foreign capital to enhance agricultural value chains, possibly due to strategic policies facilitating technology and expertise inflows, as [6] noted. Conversely, the negative coefficients observed in Vietnam (-0.083) and Thailand (-0.056) suggest structural or regulatory barriers that might limit the positive impact of FDI, a challenge addressed in financial integration studies [33]. The significance of the agricultural land area is profound in Indonesia and Thailand, with positive coefficients (6.219** and 6.837**), indicating that extensive agricultural lands are integral to value chain enhancement, confirming [20]'s assertion on the economic importance of land resources in developing regions. However, Malaysia exhibits a negative impact (-1.273*), reflecting a shift towards industrialization, echoing Sunghun Lim's [2] work on economic transformations affecting traditional sectors.

Regarding inland waters, their importance is markedly significant in the Philippines, where the high positive coefficient (18.473**) underscores their vital role in supporting agriculture through irrigation and aquaculture, resonating [23]. On the other hand, Indonesia's negative impact (-3.760**) suggests potential overuse or mismanagement of water resources, which could undermine agricultural productivity, a concern highlighted in discussions on sustainable water management [34]. Trade balance food emerges as a strong driver in Vietnam (2.291**) and Thailand (1.406**), signifying their robust agricultural export capacities, aligning with [4] observations on the influence of trade surpluses in reinforcing agricultural resilience.

The R-squared values are particularly high for Thailand (0.937) and Vietnam (0.948), indicating a substantial explanatory power of the model in these regions, suggesting that the identified variables effectively capture the key drivers underpinning agricultural value chain dynamics.

4. Conclusions

The global food system has undergone significant changes in recent years, shifting from a primarily domestic focus to a more interconnected network. Countries now specialize in different stages of the food production process, from growing crops to processing and distributing food products. The interconnected nature of global agriculture value chains can make countries vulnerable to risks like fluctuating prices, supply chain disruptions, and trade restrictions. By understanding these factors, policymakers and stakeholders can develop strategies to ensure that food is accessible, affordable, and nutritious for everyone.

Using geographically weighted panel regressions, we investigate the drivers of global agriculture value chains in ASEAN. The study identifies tariffs as a significant factor in Indonesia, Singapore, and Thailand, where they play a protective role, especially in Thailand, which benefits as a major agricultural exporter. This aligns with strategic trade theories that

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suggest tariffs can help manage international competitiveness by safeguarding domestic industries. However, tariffs appear less significant in Malaysia and the Philippines, prompting a closer look at alternative economic policies that steer these countries' agricultural sectors.

Foreign Direct Investment (FDI) emerges as a crucial determinant, positively impacting Malaysia due to a conducive investment climate but less favourable outcomes in Vietnam and Thailand, suggesting regulatory or market barriers impeding effective FDI integration into agricultural enhancements. This observation is consistent with economic literature such as (31) which discusses the importance of regulatory frameworks for optimizing FDI benefits. Regarding agricultural land area, it proves to be a critical asset in Indonesia and Thailand, emphasizing its role in enhancing productivity, much in line with [21], who underscore the significance of land in agricultural development. However, a negative association in Malaysia points to a transition towards more industrialized economies, supporting [2] discussion on structural transformation.

Inland waters, including rivers, lakes, and estuarial zones, are vital in the Philippines, where they significantly bolster agricultural activities, aligning with [23]'s emphasis on water resources in agricultural productivity. Conversely, in Indonesia, challenges with water resource management are underscored by the negative correlation, warning of potential inefficiencies that echo sustainable management concerns outlined by [34]. Trade balance food is crucial in reinforcing agricultural value chains in Thailand and Vietnam. It highlights their significant roles as agricultural exporters in the global market, consistent with [4] findings on trade surpluses reinforcing agricultural resilience.

These findings lead to several policy recommendations. First, optimizing tariffs to maintain a balance between protection and international market participation in Indonesia, Singapore, and Thailand. Second, promoting favourable environments for FDI by streamlining regulatory frameworks to attract and integrate foreign capital, particularly in Vietnam and Thailand. Also, maintain land use for agriculture policies to maximize productivity while accommodating economic shifts. Lastly, promoting sustainable management of inland waters is essential for ensuring environmental preservation alongside agricultural efficiency.

Despite its insights, the study faces limitations in scope, focusing only on select ASEAN countries, which may limit its generalizability. Considering broader variables, such as socio-political influences and global trends like climate change, adds depth and complexity to the findings. Future research can expand geographically to capture more comprehensive insights across different ASEAN nations or regions globally, enriching the comparative analysis. A research agenda integrating dynamic modelling to account for temporal and technological changes could provide richer longitudinal insights into agricultural value chain developments. Additionally, considering socio-political contexts and their interaction with economic drivers can offer a nuanced understanding of how policy decisions shape agricultural outcomes. Thus, the study uncovers the underlying mechanisms shaping these agricultural sectors and sets the

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stage for future exploration and policy enhancements that sustain growth, competitiveness, and resilience in the face of evolving challenges in the global agricultural landscape.

Interventions targeting the key drivers of global agriculture value chain participation—such as trade policy, foreign direct investment, resource endowments, and efficient water and land management—will significantly enhance regional development in ASEAN. By addressing these factors, countries can increase agricultural productivity and benefit from higher integration into the global agricultural value chain. Tailored policy actions that enhance GVC participation will strengthen national economies and promote greater economic integration within the ASEAN region, contributing to shared prosperity and more resilient agricultural sectors across member states.

Referensi

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