

Article

Research on the Measurement and Network Construction of Agricultural Product Logistics Level in Thailand

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Abstract

With the rapid development of the Thai economy and the continuous improvement of national living standards, the Thai people's demand for freshness, quality, and diversity of agricultural products is constantly increasing. Efficient agricultural product logistics can not only ensure the supply and quality of agricultural products, but also promote the optimization of resource allocation and logistics infrastructure construction, with direct implications for reducing food loss, lowering energy consumption, and enhancing the resilience of regional food systems—key dimensions of sustainable agricultural development. In order to analyze the development status of agricultural product logistics in Thailand, the paper constructed an evaluation system consisting of four dimensions and seven indicators. Factor analysis and natural break point method were used to measure the development level of agricultural product logistics in 77 provinces of Thailand from 2012 to 2023, and the spatial pattern evolution characteristics were analyzed. The research conclusion is as follows: (1) From 2012 to 2023, the comprehensive score of agricultural product logistics in Thailand increased from 24.01 to 30.89, indicating a significant enhancement in overall strength; (2) the logistics level of agricultural products in various provinces of Thailand shows heterogeneous characteristics; (3) by calculating the strength of agricultural product logistics attraction between cities, the Central Plains Agricultural Product Logistics Circle centered on Bangkok, the Northern Plains Agricultural Product Logistics Circle centered on Chiang Mai Province, and the Southern Logistics Circle centered on Pattani and Yala provinces were determined.

Keywords: Thailand; agricultural product logistics; network construction; spatiotemporal evolution



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1. Introduction

Thailand, as a major agricultural country in Southeast Asia, holds a significant position in the global agricultural export market, with rice, natural rubber, tropical fruits, and other products being highly competitive in international supply chains. In 2024, Thailand's total exports of agricultural and processed agricultural products reached USD 52.19 billion, a 6% increase year-on-year, accounting for 17.4% of total exports. However, given the complexity of the global trade environment, the upgrading of consumer demand, and the acceleration of regional economic integration, the efficiency of agricultural product circulation has become a key factor affecting the sustainable development and international

competitiveness of Thailand's agriculture. In May 2018, the Eastern Economic Corridor (EEC) Special Economic Zone Act was officially implemented following royal endorsement. The act identifies logistics and aviation as key industries prioritized by the Thai government for development and vigorously promotes the construction of high-speed rail and highway infrastructure. In this context, the efficient upgrading of the agricultural product logistics system not only affects agricultural output growth but is also directly linked to Thailand's food security, optimal resource allocation, and regional economic resilience.

At present, Thailand's logistics industry is accelerating its emergence as a regional logistics hub, leveraging the Eastern Economic Corridor (EEC) and the development of major infrastructure such as the China–Thailand Railway. Its development focuses on the systematic integration of railway, waterway, and airway networks, aiming to establish an efficient multimodal transport system. By 2023, Thailand's total railway mileage reached 5109 km, with an annual freight volume of 11.456 million tons. The Bangkok–Nakhon Ratchasima section of the China–Thailand Railway, as a core cross-border corridor, connects to Yunnan Province via the China–Laos Railway, forming a complete rail chain from Kunming to Vientiane and Bangkok. This route reduces transit time by over 50% compared to traditional land transport, providing a low-cost, high-efficiency land corridor for northern production areas to access the Chinese market and substantially meeting the cross-border transportation demand for Thai agricultural products. In water transport, Thailand has developed a cost-effective transportation system utilizing its inland waterway network and coastal port clusters. Of the country's 47 ports, Laem Chabang Port and Bangkok Port serve as core hubs, with maritime routes covering major agricultural import markets such as China, Japan, and the United States. According to the Port Authority of Thailand, the total seaport throughput in fiscal year 2024 was approximately 8.1 million TEUs, with rubber, cassava, tropical fruits, and other agricultural products accounting for over 30%. In addition, the Mekong River waterway connects Mekong subregion countries such as Laos and Cambodia, facilitating the distribution of agricultural products like rice and corn from northeastern Thailand to neighboring markets. In air transport, Thailand's air cargo throughput reached 278,000 tons in 2023. Although it accounts for only 0.02% of domestic cargo and 0.3% of international cargo due to high costs, it serves as a supplementary mode for cross-border transportation of high-value fresh agricultural products.

However, Thailand's agricultural product logistics system still faces three prominent problems. The first concerns the bottleneck of circulation efficiency. The existing logistics network struggles to reconcile the timeliness requirements of high-value-added agricultural products with the cost-efficiency demands of bulk agricultural products, which fails to align with the prevailing trends toward premium quality and just-in-time consumption. Second, spatial distribution remains highly imbalanced. Logistic resources are concentrated in the Eastern Economic Corridor (EEC), while the northern and northeastern characteristic production areas, hindered by underdeveloped transport infrastructure, face severe constraints in moving high-quality agricultural products to major markets. Third, network coordination remains inadequate: the intermodal transport connection mechanism is inefficient, and there is a lack of quantifiable evidence regarding the intensity of inter-provincial logistics linkages, which constrains the efficiency of the entire circulation chain.

In summary, three key research questions emerge: what is the current level of agricultural product logistics development in Thailand? How has its spatial pattern evolved over time? And how can inter-provincial logistics networks be optimized to improve overall efficiency? Addressing these questions is of great practical significance for Thailand in breaking through the core bottlenecks of agricultural product logistics, optimizing resource allocation, enhancing international competitiveness, and supporting sustainable agricultural development. Therefore, this paper measures the development level of agri-

cultural product logistics across 77 provinces of Thailand from 2012 to 2023 using factor analysis and the natural breakpoint method, and analyzes the characteristics of its spatial pattern evolution. Based on this, the gravity model is employed to calculate the intensity of inter-provincial agricultural product logistics linkages, upon which Thailand's logistics network is constructed.

The innovations of this article may be in the following two aspects. In terms of theoretical innovation, this paper constructs an analysis framework for the spatial network of agricultural product logistics that integrates factor analysis, natural breakpoints, and gravity models, revealing the evolution of the spatial pattern of agricultural product logistics in Thailand and enriching empirical research on regional agricultural product logistics networks. In terms of practical innovation, this paper is oriented towards the actual demand of agricultural product logistics in Thailand and provides a basis for policy-making by measuring the development level of agricultural product logistics in multiple regions.

Beyond measuring logistics development levels, this study also contributes to the sustainability discourse. The spatial heterogeneity in logistics capacity identified in this paper has direct implications for sustainable agricultural development: regions with under-developed logistics infrastructure typically face higher post-harvest loss rates, increased transportation costs per unit, and limited market access for smallholder farmers. By identifying the spatial structure of potential logistics networks, this study provides an empirical basis for policy interventions that can simultaneously improve economic efficiency, reduce environmental footprints, and enhance social equity in logistics service access—core objectives of sustainable development.

2. Literature Review

2.1. Related Research on Logistics Network Construction

The academic community mainly explores two dimensions: network nodes and the overall network. At the research level of network nodes, scholars focus on the combination of qualitative evaluation and quantitative models. In terms of qualitative analysis, early research focused on building a systematic evaluation framework: Awasthi (2012) [1] solved the site selection ranking problem through the AHP fuzzy TOPSIS combination model; Catalano et al. (2014) [2] introduced a game model to explore the dynamic balance between node location and regional resources. In recent years, Mishra et al. (2019) [3] introduced the Hesitation Fuzzy Set (HFS) theory to address the common issues of information ambiguity and multi criteria conflicts in decision-making environments, and constructed a smart logistics node evaluation system that includes digital capability indicators. Yesilcayir et al. (2024) [4] further improved the operability of node location selection in disaster logistics scenarios by combining intuitive fuzzy AHP with GIS spatial analysis strategy, from the three stages of “weight determination—scheme sorting—spatial screening”. In terms of quantitative analysis, the research focus has shifted from single cost optimization to collaborative decision-making under complex constraints. Miranda et al. (2004) [5] and Alumur et al. (2012) [6] validated the effectiveness of heuristic algorithms and mixed integer programming models in site selection under unconstrained and capacity constrained conditions, respectively; De Keizer et al. (2015) [7] combined simulation techniques to determine the optimal layout. Subsequent studies have placed greater emphasis on the comprehensive consideration of “uncertainty, resilience, and cross-border collaboration”: Badyal et al. (2023) [8] and Li et al. (2024) [9] respectively adopted two-stage stochastic programming and robust optimization methods, focusing on addressing the issue of network resilience under demand fluctuations and hub interruption risks; Andaryan et al. (2024) [10] proposed an improved taboo search algorithm for large-scale cases to enhance solving efficiency; Wang et al. (2025) [11] developed a hierarchical mul-

timodal transport hub location model for cross-border logistics scenarios, quantifying the coupling effects of congestion costs and economies of scale on hub level layout in cross-border channels.

In the study of overall network structure, scholars focus on the morphological evolution and performance differences between hub and spoke and straight through networks. The classic research of Nakatsu et al. (2005) [12] and Bowen (2012) [13] established the core position of hub and spoke networks in reducing the number of connections and improving aggregation efficiency. Afterwards, academic research continued to deepen the applicability verification of this structure in modern complex logistics systems: Ghaffarinasab et al. (2023) [14] constructed a risk averse single allocation hub location model based on mean CVaR, and analyzed the changes in hub configuration and cargo flow organization under the conditions of uncertain OD flow and flow-dependent economies of scale in transportation costs. Zhou et al. (2022) [15] constructed a hub and spoke network design model for road railway multimodal transport for China Europe freight trains, introducing “optional service levels” and incorporating environmental parameters and economies of scale into structural optimization. Huang et al. (2022) [16] explicitly incorporated port interruption and congestion costs into the hub and spoke network design in the liner transportation network, indicating that reliability and congestion constraints will drive hub backup and path replacement strategies into the structural optimization framework. However, with the increasing complexity of the supply chain environment, Alumur et al. (2021) [17] pointed out in their review that the current optimization focus has shifted from static costs to dynamic congestion, multimodal collaboration, and resilience reconstruction. Based on this, the latest research shows a clear trend of “hybridization and refinement”. Real et al. (2021) [18] proposed a hybrid network design that allows for the coexistence of hub and non-hub nodes to balance agglomeration economies and direct demand; Wang et al. (2024) [19] and Kweon et al. (2024) [20] respectively introduced traffic delay costs and sorting organization constraints, deepening the research on the structural trade-off of hub and spoke networks under the background of e-commerce explosion. In addition, Li et al. (2023) [21] constructed a dual objective optimization model for epidemic emergency transportation to meet the special needs of specific scenarios, highlighting the network’s ability to quickly reconstruct under impact situations; Yin et al. (2023) [22] optimized the spatial connectivity of the port multimodal transport network from the perspective of port hinterland integration, using a gravity model.

Existing research mostly focuses on optimizing the design of networks, while there is a lack of coherent empirical analysis from measuring the level of development, quantifying the strength of inter-provincial connections, to identifying spatial network structures for logistics systems already in operation in reality.

However, most of the above studies are based on developed economies and large emerging economies such as China. Research on logistics network evolution in developing Southeast Asian countries is still limited. The formation of logistics hubs in developing economies is more constrained by institutional supply and infrastructure gaps, and the general network optimization framework cannot be directly applied.

2.2. Related Research on Agricultural Product Logistics Network

Due to the particularity of agricultural product logistics networks and their perishable characteristics, research in recent years has generally integrated decision-making processes such as site selection, inventory, and transportation routes to explore how to improve the circulation efficiency of agricultural product logistics networks. Liu et al. (2021) [23] incorporated freshness and carbon emissions into a multi-objective trade-off framework for site selection, inventory, and path optimization, emphasizing the significant impact of time

sensitive parameters such as transportation speed on system efficiency. Shaabani (2022) [24] pointed out that linking inventory management with vehicle routing can systematically improve timeliness and loss performance around the problem of inventory routing for perishable goods, and summarized the main evolution of demand types, objective functions, and solution methods. Mousavi et al. (2022) [25] introduced uncertain demand and freshness penalty terms in the stochastic production path model of production inventory distribution integration, characterizing the constraint mechanism of perishability on collaborative decision-making between production and distribution. Song and Wu (2023) [26] incorporated the joint decision-making of location, inventory, and routing in a three-tier supply chain into a unified framework, and compared the impact of allowing direct delivery from the supply side to the retail side on cost and efficiency, reflecting the potential advantages of direct delivery in high efficiency scenarios. Mohammadi et al. (2023) [27] constructed a multi-objective location inventory model that includes price-related demand and spoilage rate, emphasizing the need for coordinated adjustment of network configuration and replenishment strategy when demand is sensitive to freshness. He et al. (2024) [28] proposed a robust optimization model for the multi cycle inventory routing problem of perishable goods with uncertain demand, considering both product lifespan and gradual deterioration, to enhance the stable distribution capability of the network in fluctuating environments. In the context of fresh food e-commerce, Guo et al. (2025) [29] established a location inventory model that considers quality degradation and differences in online and offline demand for the front-end warehouse model. They pointed out that optimizing warehouse network coverage and inventory strategies can improve performance service levels while reducing logistics costs.

Cold chain logistics, as an important branch of agricultural product networks, has also received widespread attention. At the network level, Jouzdani and Govindan (2021) [30] take dairy products as an example and incorporate uncertain shelf life, refrigeration utilization, energy consumption, and congestion into network design, demonstrating that cold chain layout should not only consider transportation costs, but also take into account the costs of refrigeration and urban transportation. Orjuela-Castro et al. (2022) [31] designed a perishable food logistics network from a multi category and multi-level perspective, explicitly considering delivery time and losses, providing a directly applicable modeling framework for the hierarchical organization of cold chain networks. In scenarios with greater risk and volatility, Arabsheybani et al. (2024) [32] used data-driven robust optimization to design a cold chain network for livestock products and perishable goods, placing sustainable goals and uncertainty in the same decision, emphasizing the need for the cold chain to leave room for risk resistance adjustments. Accorsi et al. (2025) [33] proposed an energy-saving cold chain network design concept for fresh food based on energy consumption, explaining why the same network structure has different operating costs in different regions using the difference in environmental and refrigeration energy consumption. At the delivery level, Ding et al. (2025) [34] incorporated the risk of freshness compliance caused by random arrival time into low-carbon cold chain path decision-making, while considering cost and carbon emissions, which is closer to the reality of fresh food delivery that is “afraid of being late and afraid of not being fresh”. In response to supply chain shocks, Ran et al. (2025) [35] incorporated supply disruptions and demand fluctuations into the optimization of fresh cold chain networks, using resilience strategies to balance service levels, costs, and emission reduction targets. The review research also summarizes these directions. Iyer and Robb’s (2025) [36] systematic review points out that the key points repeatedly emphasized in the cold chain optimization model are mainly focused on temperature control constraints, energy consumption emissions, and corruption loss risks. Network design and distribution planning often need to be considered in conjunction.

On the one hand, existing research focuses on node location and network structure optimization, continuously incorporating factors such as congestion, resilience, and collaboration into the model. On the other hand, in response to the perishability of agricultural products and cold chain constraints, a more integrated approach of site selection, inventory, and routing is adopted, emphasizing the balance between timeliness, loss, and energy consumption reduction. However, overall, the relevant achievements still focus on optimizing the design of the network, and there is a lack of continuous empirical analysis from measuring development level to quantifying intergovernmental connections, and then to identifying spatial network structures for logistics systems that have already been operated in reality.

For Thailand, existing studies are limited to macro policy interpretation and single-region case analysis, lacking nationwide quantitative spatial network research. Weerapong et al. (2026) [37] measured multimodal export logistics performance within Thailand's Eastern Economic Corridor under institutional constraints, yet only focused on eastern industrial zones without nationwide spatial comparison. Kuaites and Thungwha (2025) [38] analyzed Thailand's agri-logistics strengths and weaknesses via industrial survey rather than cross-country quantitative comparison, failing to capture provincial spatial disparities. However, no one has conducted systematic province-level measurement and spatial network identification, which constitutes the entry point of this paper.

Empirical studies on logistics network evolution in developing countries are scarce. Adopting gravity models, Wongmonta (2021) [39] explored China–Thailand agricultural fruit trade flows, confirming GDP expands bilateral trade while geographic distance creates significant trade resistance. This study extends this gravity-model analytical framework to identify provincial-level logistics spatial correlation networks within Thailand.

Based on this, this article will conduct measurement and network construction research using Thai intergovernmental data as the basis, providing a basis for subsequent optimization.

3. Measurement of the Development Level of Agricultural Product Logistics in Thailand

Based on the actual development of agricultural product logistics in Thailand, this study constructs a Regional Economic Development Level, Agricultural Product Development Conditions, Logistics Development Level, Informatization Level. The indicator system for the development level of agricultural product logistics in 77 provinces in Thailand, consisting of seven indicators across four dimensions, is shown in Table 1. The sample range of primary indicators is from 2012 to 2023.

Table 1. Measurement index system for the development level of agricultural product logistics in Thailand.

Primary Indicators	Secondary Indicators	Variable Symbol	Unit
Regional Economic Development Level	Gross Regional Product (GRP)	X ₁	Millions of Baht
	Gross Output Value of the Tertiary Industry	X ₂	Millions of Baht
Agricultural Product Development Conditions	Sown Area of Crops	X ₃	Rai
	Number of Farming Households	X ₄	Household
Logistics Development Level	Number of Vehicle Registration	X ₅	Vehicles
	Highway Freight Volume	X ₆	Ton
	Cold Chain Capability	X ₇	Number
	Logistics Cost	X ₈	Ton/Km
Informatization Level	Number of Desktop Personal Computer	X ₉	Household/Machine
	Number of Internet users aged 6 and above	X ₁₀	Person

3.1. Regional Economic Development Level

Regional Economic Development Level is an important external environmental factor that affects the operation and development of agricultural product logistics systems. For each province in Thailand, the level of regional economic development not only reflects the comprehensive strength of the local economy, but also directly affects the scale of agricultural product logistics demand, logistics efficiency, and so on. When measuring the regional economic development level of various provinces in Thailand, this article selects two sub indicators, Gross Regional Product (GRP) and Gross Output Value of the Tertiary Industry, for comprehensive characterization. On the other hand, GRP is a core indicator for measuring the overall development level of various provinces in Thailand, which can comprehensively reflect the level of economic activity in the region. GRP is a high-level government that usually has more complete logistics infrastructure conditions, which can provide solid support for the storage, transportation, and distribution of agricultural products. On the other hand, the total value of the tertiary industry reflects the level of development of a region's service industry and the degree of optimization of its economic structure. The higher the proportion of the gross domestic product of the tertiary industry in a region, the more it usually means that the economic structure of the region is tending towards modernization and upgrading, which means more consumer demand and higher consumption capacity.

3.2. Agricultural Development Conditions

The conditions for agricultural development directly affects the production, supply, and consumption of agricultural products, and are an important foundation for evaluating and promoting high-quality agricultural development. This article selects two sub indicators, the Sown Area of Crops and the Number of Farming Households, for measurement. Among them, the sowing area of crops reflects the available scale of regional agricultural land resources and is the material basis for agricultural product production. The larger the sowing area, the more abundant the agricultural production space, which is conducive to providing guarantees for the yield of agricultural products. The number of farmers engaged in agriculture reflects the scale of labor input in agricultural production. A larger number of farmers engaged in agriculture means a higher level of participation in agricultural production, which helps to provide necessary human resources for the supply of agricultural products.

3.3. Logistics Development Level

The level of logistics development reflects the comprehensive transportation capacity and basic guarantee level of a region in the logistics industry. Four indicators are selected to measure this level. The number of civilian cargo vehicles directly reflects the actual transportation capacity of regional logistics transportation vehicles; the higher the value of this indicator, the more vehicles available for cargo transportation, and the stronger the logistics transportation capacity. Highway freight volume reflects the scale of agricultural product transportation activity, with a larger volume indicating higher logistics activity. Considering the close connection between airports and cold chain infrastructure (Jantapirak et al., 2026) [40], cold chain capacity is proxied by the number of airports in each province, reflecting the ability to handle temperature-sensitive agricultural products through air transport. Logistics cost is measured by road freight turnover, where a higher value implies greater economies of scale and thus lower unit logistics costs.

3.4. Informatization Level

The construction of information infrastructure in the level of informatization provides basic information acquisition, processing, and transmission conditions for the development of agricultural product logistics. This study selected Number of Desktop Personal Computer, Number of Internet users aged 6 and above as specific sub indicators. Among them, the number of desktop personal computers reflects the level of hardware infrastructure configuration for regional informatization, providing necessary hardware support for the operation of agricultural product logistics information systems. The number of Internet users aged 6 and above directly reflects the popularity of the Internet and the level of residents' use of information technology, which promotes the docking of agricultural product supply and demand information and the optimization of logistics resource allocation.

3.5. Data Sources and Processing

3.5.1. Data Sources

The data used in this study are obtained from official statistical sources in Thailand, covering 76 provinces and one special administrative area (Bangkok). Specifically, the data are derived from the statistical yearbooks and official surveys published by the Office of the National Economic and Social Development Council (NESDC), Office of the Prime Minister; the Office of Agricultural Economics, Ministry of Agriculture and Cooperatives; the National Statistical Office under the Ministry of Digital Economy and Society, including the Household Survey on the Use of Information and Communication Technology; and the Department of Land Transport, Ministry of Transport.

3.5.2. Data Processing

This paper adopts the factor analysis method. This method can simplify a large number of observed variables into fewer factors, which can explain most of the variability in the original dataset, thereby simplifying the data structure and making the data easier to understand and interpret. Meanwhile, factor analysis can help us discover the potential structures hidden behind the data, allowing us to deeply understand the interrelationships between variables. The calculated factor scores can be used for the comprehensive evaluation and classification of samples. The steps of the factor analysis method are as follows:

Step 1: Data Standardization. This paper adopts the min–max normalization method, and its formula is as follows:

$$Z_i = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

where X_i represents the original data and Z_i represents the standardized data.

Step 2: Factor Analysis Testing: During the analysis, IBM SPSS Statistics 27.0 is used to perform the KMO and Bartlett's Test of Sphericity on the standardized original data. If the KMO value is 0.844, greater than 0.5 and the p -value of Bartlett's Test of Sphericity is less than 0.05, the data is suitable for factor analysis. This paper tested the data of all 77 provinces over the 12-year period from 2012 to 2023 based on thirteen indicators. The KMO values were all greater than 0.5 and the p -values were all less than 0.001, indicating that the selected data is suitable for factor analysis. The KMO and Bartlett's test results are shown in Table 2.

Table 2. KMO and Bartlett's test results.

KMO Value		0.844
Bartlett's Test	Approximate Chi-Square	22,274.383
	Degree of Freedom	45
	p Value	0.000

Step 3: Common Factor Extraction: By performing factor analysis on the standardized original data, principal component factors are extracted based on the principle that eigenvalues are greater than 1. General research suggests that when the cumulative variance contribution rate is higher than 80%, it can cover the data characteristics of all variables and is representative. In the five-year data of this paper, the principal component factors extracted each year all exceeded 85%. Specifically, the eigenvalue of F1 is 6.638, the eigenvalue of F2 is 1.997, and the cumulative variance interpretation rate after rotation is 86.350%.

Step 4: Factor Rotation: The Varimax rotation method is used to rotate the factors, making the principal component loadings closer to 0 or 1 for enhanced interpretability. After rotating the data for each year, it is observed that Gross Regional Product (X1), Gross Output Value of the Tertiary Industry (X2), Number of Vehicle Registrations (X5), Highway Freight Volume (X6), Logistics Cost (X8), Number of Desktop Personal Computers (X9), and Number of Internet users aged 6 and above (X10) all exhibit relatively high loadings on Common Factor 1 and are primarily explained by the first component, so this factor is summarized as F1: Regional Economic and Informatization Development Factor. Meanwhile, Sown Area of Crops (X3), Number of Farming Households (X4), and Cold Chain Capability (X7) show high loadings on Common Factor 2 and are mainly explained by the second component; thus, this factor is named F2: Agricultural Production and Supply Capacity Factor. Table 3 shows the component score coefficient matrix, while Table 4 presents the rotated component loading matrix using the Varimax method with Kaiser normalization.

Table 3. The matrix of component score coefficients.

	F1	F2
X1	0.150	−0.019
X2	0.149	−0.008
X3	−0.017	0.462
X4	−0.011	0.476
X5	0.147	0.063
X6	0.149	−0.022
X7	0.022	0.222
X8	0.149	−0.022
X9	0.144	0.000
X10	0.136	0.077

Table 4. Rotated load matrix.

	F1	F2
X1	0.993	
X2	0.991	
X8	0.990	
X6	0.988	
X5	0.976	
X9	0.954	
X10	0.901	
X4		0.951
X3		0.923
X7		0.444

In addition, it can be found that the factor load of the cold chain index is lower than other variables. The reason why this index is retained is that, on the one hand, the core theme of this study is the logistics level of agricultural products, and the cold chain transportation capacity is an indispensable component of the temperature sensitive

agricultural product logistics system. On the other hand, in exploratory factor analysis, 0.3 or 0.4 is usually used as the minimum retention criterion for factor loading. In this study, the factor loading of the cold chain index was 0.444, which is lower than other variables but still higher than the conventional threshold, indicating a meaningful association between it and potential factors.

Step 5: Factor Score Calculation and Result Analysis: The Component Score Coefficient Matrix is obtained using the Varimax method in SPSS software. The composite score of agricultural logistics in Thailand is derived by weighting each common factor by its proportion of variance contribution, formulated as $\text{Composite Score} = 66.383\% \cdot F1 + 19.966\% \cdot F2$.

To ensure the robustness of factor analysis, this article conducts sensitivity analysis on the samples from two aspects. Firstly, change the iteration count. When using the maximum variance method for rotation, change the maximum convergence iteration count from 25 to 50 and recalculate. Secondly, replace the rotation method by replacing the original maximum variance method with the equal maximum method. The results showed that there was no substantial change in the factor attribution and load direction of each indicator, proving that the factor analysis structure in the previous section is robust.

To test the robustness of our weighting approach, we employed the entropy weight method as an alternative to factor analysis for constructing the composite indicator. The results show that the top ten cities ranked by average logistics capacity for agricultural products during 2012–2023 are Bangkok, Surat Thani, Rayong, Samut Prakan, Nakhon Ratchasima, Tak, Chiang Mai, Chon Buri, Songkhla, and Mae Hong Son. This ranking is largely consistent with that derived from the factor analysis, confirming that our findings are not sensitive to the specific weighting method adopted.

3.5.3. Analysis of the Comprehensive Development Level of Agricultural Product Logistics

Based on the factor analysis method, the development level of agricultural product logistics in Thailand from 2012 to 2023 and the ranking of agricultural product logistics levels for each year were calculated. The results are shown in Figure 1.

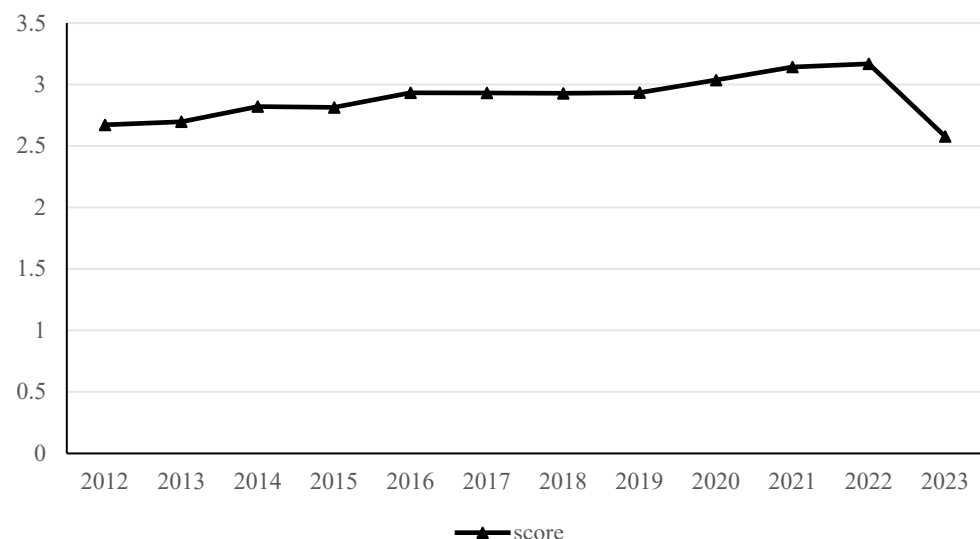


Figure 1. The development level of agricultural product logistics in Thailand from 2012 to 2023.

Figure 1 shows the development score of agricultural product logistics in Thailand from 2012 to 2023. Overall, the development level of agricultural product logistics in Thailand showed an upward trend before 2022, but experienced a decline in 2023. In 2012, the score was the lowest at 2.67, but it has been steadily increasing year by year, reaching its highest value of 3.17 in 2022. This indicates that from 2012 to 2022, Thailand's

agricultural product logistics experienced coordinated development in various aspects. The improvement of logistics may be attributed to various factors, including regional economic growth, strengthening of logistics infrastructure, and advances in information technology, all of which contribute to the overall improvement of agricultural logistics development. The significant decline in the score in 2023 is mainly due to the significant contraction of Thailand's agricultural product exports due to weak global demand, as well as the sustained high logistics costs, which have had a significant impact on the overall vitality of the logistics system. This reflects that the development of Thailand's agricultural product logistics still relies heavily on the external market environment, and its internal stability needs to be further improved.

In addition, we introduce the Granger causality test, which aims to verify whether the four dimensions of regional economic development level, agricultural product development conditions, logistics development level, and informatization level have a predictive causal effect on the logistics level of agricultural products in Thailand. Therefore, the research conclusions not only rely on the static correlations revealed by factor analysis, but also on the testing of temporal relationships between variables, thereby enhancing the overall credibility of the analysis framework. The results show that the *p*-values are significant at the 5% level, leading to the rejection of the null hypothesis. This indicates that the improvement in Thailand's agricultural product logistics level can be attributed to Regional Economic Development Level, Agricultural Product Development Conditions, Logistics Development Level, and Informatization Level.

As shown in Table 5 the overall development level of agricultural product logistics in Thailand showed an upward trend from 2012 to 2023, with a decline in 2023. Among them, F1 mainly reflects the development of regional economy and information technology. In 2012, the F1 score was -1.137 , showing a fluctuating upward trend. This indicates significant progress in logistics infrastructure, such as a significant increase in the number of civilian freight vehicles. The growth of Internet users, as well as the increase in regional GDP and the total value of the tertiary industry, may have contributed to the improvement of logistics infrastructure. F2 reflects the conditions related to agricultural production and supply. In 2022, the F2 value is the highest, at 20.225, and will decrease to 16.962 in 2023. This indicates that there is improvement in areas such as crop planting area and number of farmers related to agricultural supply, but they are also susceptible to external environmental influences. The overall F-value has also increased year by year, from 2.671 in 2012 to 3.168 in 2022, but dropped to 2.577 in 2023, reflecting the volatility of Thailand's agricultural product logistics development.

Table 5. Factor scores and comprehensive development level of Thailand's agricultural product logistics from 2012 to 2023).

Rank	Year	F1	Year	F2	Year	F
1	2012	-1.137	2012	17.159	2012	2.671
2	2013	-1.164	2013	17.376	2013	2.696
3	2014	-1.078	2014	17.707	2014	2.820
4	2015	-1.161	2015	17.949	2015	2.813
5	2016	-1.119	2016	18.409	2016	2.932
6	2017	-1.220	2017	18.735	2017	2.931
7	2018	-1.283	2018	18.930	2018	2.928
8	2019	-1.289	2019	18.976	2019	2.933
9	2020	-1.230	2020	19.293	2020	3.036
10	2021	-1.260	2021	19.925	2021	3.142
11	2022	-1.311	2022	20.225	2022	3.168
12	2023	-1.219	2023	16.962	2023	2.577

4. Analysis of the Spatial and Temporal Evolution of Agricultural Product Logistics Development Level in Thailand

Logistics Development Level of Each Province in Thailand and the Bangkok Metropolis

This article calculates the development level of agricultural product logistics in 77 provinces in Thailand from 2012 to 2023 using factor analysis. Table 6 reports the top 10 and bottom 10 levels of agricultural product logistics development in each province of Thailand in 2012 and 2023.

Table 6. The development level of agricultural product logistics in the top 10 and bottom 10 provinces in Thailand.

Rank	Provinces	2012	Provinces	2023	Provinces	Average
1	Bangkok	45.360	Bangkok	65.779	Bangkok	56.334
2	Samut Prakan	8.686	Chon Buri	12.971	Samut Prakan	9.228
3	Rayong	8.531	Nakhon Phanom	10.928	Rayong	8.969
4	Surat Thani	8.286	Rayong	10.433	Chon Buri	8.215
5	Tak	6.798	Samut Prakan	8.813	Surat Thani	7.672
6	Songkhla	6.272	Trat	8.378	Nakhon Ratchasima	7.455
7	Khon Kaen	6.251	Suphan Buri	8.140	Chiang Mai	6.685
8	Chon Buri	6.136	Sing Buri	8.054	Tak	6.612
9	Chiang Mai	6.042	Pathum Thani	6.972	Khon Kaen	6.423
10	Mae Hong Son	5.946	Chiang Mai	6.832	Songkhla	5.999
...	...	...	...	...	...	...
68	Amnat Charoen	0.539	Maha Sarakham	−1.019	Yasothon	0.600
69	Mukdahan	0.532	Amnat Charoen	−1.026	Nakhon Nayok	0.577
70	Bueng Kan	0.511	Udon Thani	−1.372	Uthai Thani	0.542
71	Sing Buri	0.502	Nakhon Si Thammarat	−1.451	Chanthaburi	0.520
72	Pattani	0.474	Nong Khai	−1.462	Mukdahan	0.483
73	Ang Thong	0.461	Phitsanulok	−1.764	Phangnga	0.474
74	Nakhon Nayok	0.364	Yasothon	−1.883	Nong Khai	0.462
75	Samut Songkhram	0.278	Chumphon	−2.893	Amnat Charoen	0.396
76	Satun	0.204	Phetchabun	−2.990	Ang Thong	0.391
77	Nong Khai	−0.436	Si Sa Ket	−4.666	Samut Songkhram	0.362

As indicated in Table 4, in 2012, the provinces with the highest levels of agricultural product logistics development in Thailand were Bangkok, Samut Prakan, and Rayong, recording scores of 45.360, 8.686, and 8.531, respectively. In contrast, the lowest-performing provinces were Nong Khai, Satun, and Samut Songkhram, with scores of −0.436, 0.204, and 0.278, respectively. These disparities highlight a pronounced imbalance in agricultural product logistics development across Thai provinces during this period. By 2023, the top three provinces were Bangkok, Chon Buri, and Nakhon Phanom, with scores of 65.779, 12.971, and 10.928, respectively. Bangkok maintained its leading position with a substantial increase, while Nakhon Phanom emerged as a new top performer. The lowest-ranking provinces in 2023 were Si Sa Ket, Phetchabun, and Chumphon, with scores of −4.666, −2.990, and −2.893, respectively, indicating a widening gap between the best- and worst-performing provinces. When considering average scores over the study period, Bangkok recorded the highest value at 56.334, whereas Samut Songkhram registered the lowest at 0.362. These findings underscore substantial inter-provincial disparities in the development of agricultural product logistics in Thailand.

This study uses the natural break point method in ArcMap 10.8.2 to analyze the agricultural product logistics capacity of Thailand in 2012, 2016, 2020, and 2023. Through the distribution and range size of different colored regions, it can be seen that there are significant differences in the logistics capacity of agricultural products in different areas of Thailand, as shown in Figure 2.

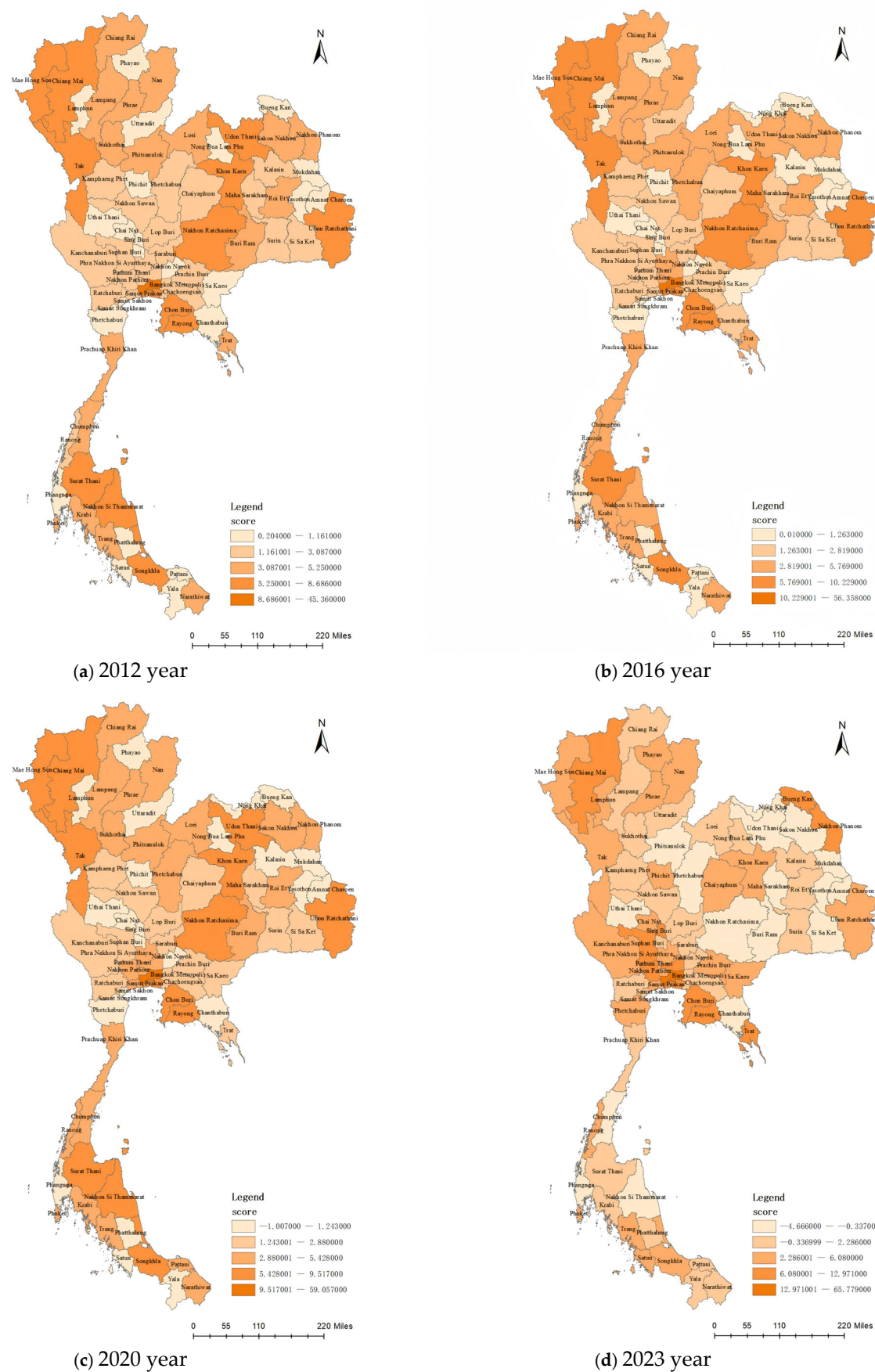


Figure 2. Map of spatial differences in the development level of agricultural product logistics in Thailand in 2012, 2016, 2020, and 2023.

The spatial distribution and size of regions shaded in different colors clearly demonstrate substantial regional disparities in agricultural product logistics capabilities across Thailand. In 2012, provinces with the highest logistics performance included Bangkok, Samut Prakan, Rayong, Surat Thani, Tak, Songkhla, Khon Kaen, Chon Buri, Chiang Mai, and Mae Hong Son. By 2023, the top-performing provinces shifted to Bangkok, Chon Buri, Nakhon Phanom, Rayong, Samut Prakan, Trat, Suphan Buri, Sing Buri, Pathum Thani, and Chiang Mai. Throughout the study period, Bangkok consistently maintained the highest logistics performance scores, with its score increasing substantially from 45.360 in 2012 to 65.779 in 2023, highlighting the capital's increasingly prominent position in the development of agricultural logistics, mainly due to its core economic and infrastructure advantages.

5. Construction of Thailand's Agricultural Product Logistics Network Based on the Gravity Model

5.1. Principles for Classifying Hub and Node Levels

Based on the ranking of the comprehensive scores for agricultural product logistics development levels in 2023 across various provinces listed in Table 6, we identified the top eight provinces—namely Bangkok, Chon Buri, Nakhon Phanom, Rayong, Samut Prakan, Trat, Suphan Buri, and Sing Buri—as the first-tier node provinces. The structural break is determined explicitly based on the score distribution. Specifically, we observed that the score drop between the eighth-ranked province (Sing Buri) and the 9th-ranked province (Pathum Thani) is 1.082. Excluding the exceptionally large gaps between the top two provinces (Bangkok and Chon Buri), this 1.082 gap is substantially larger than the average drop between other adjacent ranks, indicating a clear tier threshold at this position. Therefore, the remaining 67 cities are classified as second-tier node provinces.

5.2. Analysis of the Gravity Intensity of Agricultural Product Logistics Among Provinces in Thailand

Table 7 shows the logistics level of agricultural products in various cities in Thailand, providing a basis for calculating the agricultural product logistics network based on the gravity model in the following text.

5.3. The Gravitational Values Between Various Provinces in Thailand

By incorporating the logistics quality of each province and their comprehensive distance into the formula, the agricultural product logistics gravity intensity between each province in Thailand can be calculated. Furthermore, the natural breaks classification method is adopted to divide the agricultural product logistics gravity values of Thailand into five levels, and the specific hierarchical classification of logistics gravity relationships is shown in Table 6. The specific formula for calculating gravity is as follows: $\text{gravity} = (F_{it} \times F_{jt})/d^2$. Among them, F_{it} is the agricultural trade level of province i in year t , F_{jt} is the agricultural trade level of province j in year t , and d is the Euclidean distance between the starting and ending points, calculated from the latitude and longitude of each province.

This study categorizes gravitational interactions into five types: strong gravity, relatively strong gravity, moderate gravity, relatively weak gravity, and weak gravity, with a total of 2926 pairs of gravitational relationships. Among them, there are 2 pairs of strong gravity, 2 pairs of relatively strong gravity, 6 pairs of moderate gravity, 54 pairs of relatively weak gravity, and 2862 pairs of weak gravity. Given the large number of observations in the categories of relatively weak gravity and weak gravity, the top 20 gravity relationships were selected for analysis. Table 8 presents the classification of agricultural product logistics attraction intensity among provinces in Thailand.

Table 7. Logistics quality of agricultural products in various provinces of Thailand.

Provinces	Average	Provinces	Average	Provinces	Average
Bangkok	56.334	Prachuap Khiri Khan	3.835	Kalasin	1.437
Samut Prakan	9.228	Sukhothai	3.806	Sa Kaeo	1.397
Rayong	8.969	Nan	3.741	Maha Sarakham	1.378
Chon Buri	8.215	Trat	3.721	Phichit	1.262
Surat Thani	7.672	Phrae	3.600	Phetchaburi	1.177
Nakhon Ratchasima	7.455	Krabi	3.551	Lamphun	1.095
Chiang Mai	6.685	Narathiwat	3.527	Bueng Kan	1.061
Tak	6.612	Phra Nakhon Si Ayutthaya	3.431	Phayao	1.049
Khon Kaen	6.423	Chumphon	3.191	Sing Buri	1.045
Songkhla	5.999	Nakhon Pathom	3.157	Yala	0.942
Mae Hong Son	5.957	Ranong	3.130	Chai Nat	0.872
Ubon Ratchathani	5.910	Phetchabun	2.988	Nong Bua Lam Phu	0.861
Udon Thani	5.176	Samut Sakhon	2.688	Uttaradit	0.798
Nakhon Si Thammarat	4.997	Chachoengsao	2.570	Phatthalung	0.734
Buri Ram	4.801	Prachin Buri	2.477	Satun	0.622
Phuket	4.691	Nakhon Sawan	2.363	Yasothon	0.600
Roi Et	4.634	Saraburi	2.191	Nakhon Nayok	0.577
Chiang Rai	4.577	Surin	2.129	Uthai Thani	0.542
Nakhon Phanom	4.508	Pattani	2.115	Chanthaburi	0.520
Phitsanulok	4.401	Suphan Buri	2.068	Mukdahan	0.483
Sakon Nakhon	4.198	Kanchanaburi	1.858	Phangnga	0.474
Nonthaburi	4.191	Lop Buri	1.820	Nong Khai	0.462
Pathum Thani	4.163	Chaiyaphum	1.777	Amnat Charoen	0.396
Lampang	4.155	Ratchaburi	1.761	Ang Thong	0.391
Loei	3.858	Kamphaeng Phet	1.581	Samut Songkhram	0.362
Trang	3.836	Si Sa Ket	1.469		

Table 8. Classification of agricultural product logistics attraction intensity among provinces in Thailand.

Gravitational Type	Node-Level Logistics Gravity Relationship
Strong gravity	Bangkok-Nonthaburi; Bangkok-Samut Prakan
Relatively strong gravity	Bangkok-Chon Buri; Bangkok-Pathum Thani
Medium gravity	Bangkok-Chachoengsao; Bangkok-Nakhon Pathom; Bangkok-Nakhon Ratchasima; Bangkok-Phra Nakhon Si Ayutthaya; Bangkok-Rayong; Bangkok-Samut Sakhon
Relatively weak gravity	Chon Buri-Samut Prakan; Bangkok-Prachin Buri; Bangkok-Saraburi; Bangkok-Suphan Buri; Nonthaburi-Samut Prakan; Bangkok-Ratchaburi; Nonthaburi-Pathum Thani; Bangkok-Tak; Bangkok-Kanchanaburi; Bangkok-Khon Kaen; Bangkok-Prachuap Khiri Khan; Bangkok-Lop Buri; Chon Buri-Rayong; Bangkok-Buri Ram; Pathum Thani-Samut Prakan; Bangkok-Surat Thani; Bangkok-Trat; Bangkok-Phitsanulok; Samut Prakan-Samut Sakhon; Bangkok-Phetchaburi
weak gravity	Chiang Mai-Mae Hong Son; Chiang Mai-Lampang; Sukhothai-Tak; Buri Ram-Nakhon Ratchasima; Phitsanulok-Sukhothai; Bangkok-Trang; Nakhon Ratchasima-Samut Prakan; Khon Kaen-Roi Et; Khon Kaen-Udon Thani; Bangkok-Krabi; Bangkok-Chai Nat; Bangkok-Samut Songkhram; Chon Buri-Nakhon Ratchasima; Chon Buri-Samut Sakhon; Bangkok-Kamphaeng Phet; Nakhon Pathom-Nonthaburi; Krabi-Phuket; Nakhon Phanom-Sakon Nakhon; Khon Kaen-Nakhon Ratchasima; Nonthaburi-Phra Nakhon Si Ayutthaya

High “gravity” interactions are observed for the following province pairs: Bangkok–Nonthaburi and Bangkok–Samut Prakan. Bangkok and its surrounding provinces, such as Nonthaburi and Pathum Thani, play an important complementary role in agricultural

product logistics, reflecting their role as important agricultural product logistics gateways. Through road infrastructure such as Thai National Highway 32 (Asian Highway), not only does it make the Thai economy more dynamic (Assavavipapan and Opasanon, 2016) [41], but it also promotes more effective circulation and distribution of agricultural products.

In order to more clearly express the strength and spatial distribution characteristics of agricultural product logistics attraction between different prefectures, this paper draws an intergovernmental agricultural product logistics gravity network diagram based on the gravity model calculation results, taking each prefecture as a node and the intergovernmental logistics gravity value as the connecting weight, the thicker the line, the stronger the gravity. The logistics attraction of agricultural products between different provinces in Thailand is shown in Figure 3.

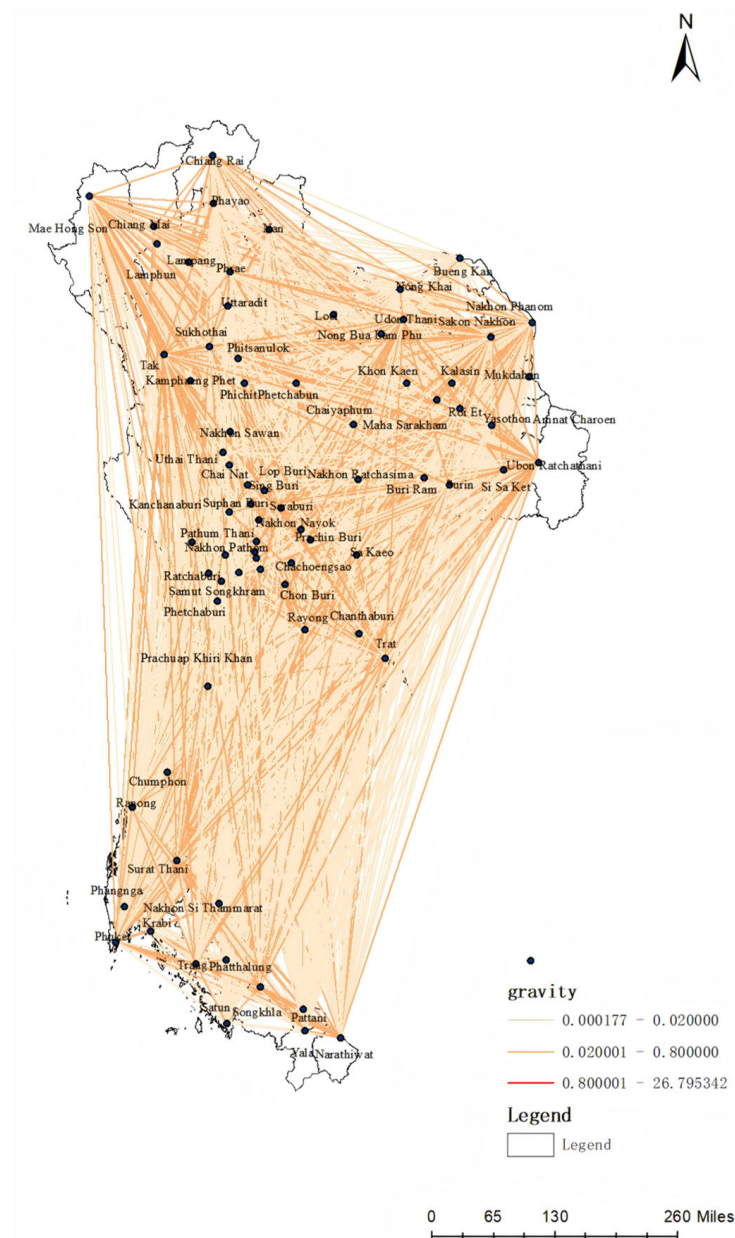


Figure 3. Analysis of potential spatial interaction gravity of agricultural product logistics among Thai provinces.

As shown in Figure 3, three major agricultural product logistics circles are identified: the central plain circle centered on Bangkok, the northern circle centered on Chiang Mai

Province, and the southern border circle centered on Pattani and Yala provinces. Within the central plain circle, the gravity values of inter-provincial agricultural product logistics are generally high, with a highly continuous spatial distribution that exhibits a clear core–periphery structure. The gravity value between Bangkok and Samut Prakan reaches 26.795, followed by those between Bangkok and Nonthaburi (21.082), Bangkok and Pathum Thani (8.286), and Bangkok and Chon Buri (7.076). These strong bidirectional logistics linkages are facilitated by well-developed road infrastructure, such as National Highway 32, which connects Bangkok with its surrounding provinces. As the largest consumer market and logistics hub in the country, Bangkok has established robust two-way logistics connections with Nonthaburi, Pathum Thani, Samut Prakan, and other adjacent provinces. In northern Thailand, an agricultural product logistics circle has emerged with Chiang Mai Province as its core and neighboring provinces as key agricultural support areas. The circle centered around Pattani and Yala provinces exhibits internal agglomeration, reflecting localized trade and distribution networks in the southern border region.

6. Conclusions and Policy Suggestions

6.1. Main Conclusions

This paper constructs an evaluation index system for agricultural product logistics development and employs factor analysis to derive the scores and rankings for Thailand's 77 provinces from 2012 to 2023. The provincial rankings derived from factor analysis, combined with the natural breakpoint method, are used to classify the node provinces into tiers, providing the main basis for identifying hub cities and axis cities. A gravity model is further employed to delineate the three major agricultural product logistics circles. The following conclusions are drawn:

- (1) The level of logistics development continues to improve, and the comprehensive strength has significantly increased. The comprehensive score of agricultural product logistics in Thailand increased from 24.01 to 30.89 from 2012 to 2023—a 28.6% increase over the 12-year period. Among them, the Regional Economic and Informationization Development factor F1 has steadily increased from 7.36 in 2012 to 9.21 in 2023 (a 25.1% increase), reflecting the synergistic effect of regional economic pull and infrastructure investment. The Agricultural Production and Supply Capacity factor F2 has rapidly increased from 16.65 in 2012 to 21.67 in 2023 (a 30.2% increase).
- (2) The logistics level of agricultural products in various provinces of Thailand shows heterogeneous characteristics. Based on the 2023 scores, Nakhon Ratchasima (1.4824), Ubon Ratchathani (1.2359), Bangkok (0.9817), Khon Kaen (0.9671), Buri Ram (0.9137), Si Sa Ket (0.9065), Udon Thani (0.8787), Surin (0.8685), Roi Et (0.8655), and Nakhon Si Thammarat (0.7554) exhibit high levels of agricultural product logistics, with a relatively complete transportation network and regional distribution function. On the contrary, Phangnga (0.1415), Satun (0.1251), Trat (0.1194), Mae Hong Son (0.1138), Nakhon Nayok (0.1086), Ranong (0.1051), Phuket (0.0829), Ang Thong (0.0758), Sing Buri (0.0641), and Samut Songkhram (0.0262) demonstrate low levels of agricultural product logistics, reflecting constraints related to limited terrain conditions, small population and market size in these provinces.
- (3) The spatial structure of agricultural product logistics in Thailand presents a multi-level potential logistics circle pattern as revealed by the gravity model analysis: a high-intensity potential agricultural product logistics circle centered on Bangkok is formed in the central plain region, a regional potential circle centered on Chiang Mai is formed in the northern region, and an inward-oriented potential agricultural product logistics circle represented by Pattani–Yala is formed in the southern border region. These findings represent spatial interaction potentials derived from the gravity

model and should be interpreted as hypotheses about regional logistics integration that await empirical validation with actual freight flow data.

The spatial heterogeneity in agricultural product logistics development identified in this study has significant sustainability implications. Provinces with higher logistics capacity—such as Nakhon Ratchasima and Ubon Ratchathani—are better positioned to reduce post-harvest losses through efficient supply chain management, lowering the carbon intensity of agricultural distribution through optimized routing, and providing smallholder farmers with access to broader markets. Conversely, provinces with lower logistics capacity face higher per-unit logistics costs, greater food loss due to inadequate storage and transportation infrastructure, and limited participation in regional and international value chains—challenges that directly affect the economic and social sustainability of agricultural communities. The potential logistics circles identified in this study provide a spatial framework for prioritizing sustainability-oriented infrastructure investments.

6.2. Policy Recommendations

Based on the above conclusions, the following three policy recommendations are proposed:

- (1) Consolidate the basic capacity of agricultural product logistics and respond to short-term downward pressure. First, in response to the port congestion and trunk transport bottlenecks exposed in 2023, priority should be given to upgrading the access and egress systems of Laem Chabang Port and Bangkok Port, optimizing the road networks for collection and distribution around ports, and alleviating chronic congestion of container truck traffic in urban port areas. At the same time, transport organization models should be optimized, and fragmented small-scale logistics enterprises should be consolidated and standardized to build an efficient logistics service system. Second, in view of rising operating costs for logistics enterprises, targeted diesel subsidies and financing support could be provided to small and medium-sized logistics enterprises to stabilize trunk transport service capacity. In the long term, investment in agricultural-logistics-related transport infrastructure should be increased, and the research, development, and application of green and intelligent logistics technologies in production areas should be accelerated to improve the modernization level of agricultural logistics technology and equipment from the source.
- (2) Implement differentiated logistics development policies according to regional resource endowments and development stages. For high-level provinces represented by Nakhon Ratchasima, Ubon Ratchathani, and Bangkok, efforts should focus on enhancing regional spillover effects and hub functions, establishing regional agricultural product distribution centers and cold chain hubs, and improving the collection and distribution capacity for bulk and fresh agricultural products. For low-level provinces in western mountainous and southern border areas (e.g., Mae Hong Son, Ranong, and Samut Songkhram), efforts should focus on improving basic transport conditions, directing public infrastructure investment toward these areas, developing local agricultural product wholesale markets, and gradually improving logistics carrying capacity to narrow the regional gap in logistics development.
- (3) Optimize the structure of the three major agricultural product logistics circles and strengthen network synergy. For the central plain logistics circle centered on Bangkok: strengthen Bangkok's role as a national agricultural logistics hub in resource integration, improve multimodal transport connections among ports, highways, and railways, and drive coordinated logistics upgrades in surrounding provinces such as Nonthaburi and Pathum Thani. For the northern logistics circle centered on Chiang Mai: position Chiang Mai as a regional logistics center, open up transport corridors connecting northern commercial towns with major agricultural producing areas in the

northeast, and facilitate cross-regional agricultural product flows. For the southern border logistics circle represented by Pattani and Yala: focus on improving cross-border logistics corridors and customs clearance efficiency at ports, enhance the external connectivity of the southern logistics circle, and reverse the current pattern of inward-oriented concentration.

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