Spatial Autocorrelation and High-Risk Area Identification of Food Poisoning in Thailand, 2003–2022

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Abstract
Food poisoning represents a persistent public health burden in Thailand, yet provincial-level spatial clustering patterns have not been comprehensively characterized over extended time series. This retrospective analytical study utilized foodborne illness incidence data from the national disease surveillance system (Report 506) of the Department of Disease Control, Ministry of Public Health, covering all 77 provinces for the period 2003–2022 (n = 2,329,463 reported cases). Provincial incidence rates (per 100,000 population) were computed annually and linked to administrative boundary polygon data. Spatial autocorrelation was assessed using the Global Moran's I statistic, and spatial cluster analysis was performed using the Local Indicators of Spatial Association (LISA) with Queen contiguity first-order spatial weights in GeoDa (version 1.14.0). Global Moran's I ranged from 0.317 to 0.522 across all study years (all p < 0.05), indicating statistically significant positive spatial autocorrelation. High–High (H–H) clusters were consistently identified in the northeastern and northern regions, with the northeastern region demonstrating 9–14 provinces per year classified. Low–Low clusters predominated in the southern region throughout the study period. The spatial clustering patterns persisted across five-year sub-periods, suggesting stable geographically determined risk factors. Findings indicate that food poisoning in Thailand exhibits non-random, geographically structured distribution attributable to inter-related socioeconomic, dietary, and food-market environmental factors. These results provide evidence for spatially targeted surveillance and intervention strategies.

Keywords: Food Poisoning, GIS, LISA, Spatial Autocorrelation, Thailand

1. Introduction

Food poisoning (foodborne illness) constitutes one of the most significant communicable disease burdens in Thailand. National surveillance through the Report 506 system of the Bureau of Epidemiology, Department of Disease Control, has documented a progressive increase in incidence rates over the past two decades. In 2022, the combined incidence of diarrhea and food poisoning was reported at 108.13 per 100,000 population, with food poisoning ranking consistently among the top ten reportable conditions [1]. The disease affects all age groups and manifests in recurrent cluster outbreaks throughout the country. Common aetiological agents include Bacillus cereus, Aeromonas spp., and Norovirus, with illness characterized by nausea, vomiting, abdominal pain, and diarrhea.

The global burden of foodborne diseases is substantial; the World Health Organization estimates approximately 600 million illness episodes and 420,000 deaths annually worldwide [2]. In Thailand, food poisoning places considerable strain on health systems through direct treatment costs and impedes progress towards Sustainable Development Goal 3 (SDG 3) ensuring healthy lives and promoting well-being for all to which Thailand is a signatory state [3]. SDG Target 3.3 specifically calls for reduction of food-borne disease incidence as part of broader communicable disease control.

In the past decade, spatial analysis methods have been increasingly applied in geographic epidemiology to characterize disease distribution patterns, identify high-risk clusters, and generate evidence for resource allocation [4]. The spatial autocorrelation approach particularly the Local Indicators of Spatial Association (LISA) statistic [5] enables identification of statistically significant spatial clusters (High–High and Low–Low), as well as spatial outliers (High–Low and Low–High), at the sub-national level. However, provincial-level spatial cluster analysis of food poisoning in Thailand using long-term data has not been previously reported. This study aimed to: (1) characterize the spatial

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autocorrelation patterns of provincial food poisoning incidence in Thailand to 20 years period from 2003 to 2022; (2) identify high-risk spatial clusters and assess their temporal stability; and (3) generate evidence to support geographically targeted surveillance and disease control planning.

2. Materials and Methods

2.1 Study Design and Data Sources

A retrospective analytical study was conducted using secondary data from the national disease surveillance system (Report 506, disease code A03) maintained by the Bureau of Epidemiology, Department of Disease Control, Ministry of Public Health, Thailand. Annual food poisoning case counts and mid-year population data were obtained for all 77 provinces for the period 2003–2022. Provincial administrative boundary data in polygon format were obtained from the Geo-Informatics and Space Technology Development Agency (GISTDA), Public Organization, Thailand. The study protocol received ethical approval from the Human Research Ethics Committee of the National Institute of Development Administration (NIDA), approval number ECNIDA 2023/0074, dated 13 June 2023.

2.2 Incidence Rate Computation and Mapping

Annual provincial incidence rates per 100,000 population (*IR*) were calculated using Equation 1:

$$IR = \frac{N_P}{N_T} \times 100,000$$

Equation 1

Where:

N_P is the number of food poisoning cases,

N_T is total population numbers.

Provincial incidence rates were linked to administrative boundary shapefiles using province codes and visualized in QGIS version 3.28.8. Incidence strata were defined using the quartile (percentile) method across all 77 provinces: low (≤ P25, ≤ 93 per 100,000), moderate (P25–P50, 94–158 per 100,000), high (P50–P75, 159–252 per 100,000), and very high (> P75, > 252 per 100,000). Maps were produced for annual data and for four five-year intervals (2003–2007, 2008–2012, 2013–2017, 2018–2022) to characterize temporal trends. Map were generated in QGIS (version 3.28.8).

2.3 Spatial Weight Matrix

A spatial weights matrix was constructed using Queen contiguity (first-order), whereby any province sharing a boundary or vertex with the target province was assigned a weight of 1 and non-adjacent provinces a weight of 0. This approach generates a spatially lagged variable representing the weighted average incidence rate of each province's neighbor’s, which is used in subsequent spatial autocorrelation analysis. All spatial operations were performed in GeoDa version 1.14.0 [5].

2.4 Spatial Autocorrelation Analysis

Global spatial autocorrelation was quantified using the Moran's I coefficient [5], ranging from −1 (perfect dispersion) to +1 (perfect clustering), with 0 indicating a random spatial distribution. Positive Moran's I values indicate spatial clustering (similar values adjacent to similar values); negative values indicate spatial dispersion. To identify statistically significant local cluster patterns, the Local Indicator of Spatial Association (LISA) Moran's I was computed for each province [5]. Five cluster types were classified: (1) High–High (H–H): province with high incidence surrounded by provinces with high incidence positive spatial autocorrelation, denoting high-risk cluster; (2) Low–Low (L–L): province with low incidence surrounded by provinces with low incidence positive spatial autocorrelation, denoting low-risk cluster; (3) Low–High (L–H): province with low incidence surrounded by provinces with high incidence negative spatial autocorrelation, indicating potential risk importation; (4) High–Low (H–L): province with high incidence surrounded by provinces with low incidence negative spatial autocorrelation, indicating potential risk exportation; and (5) Not significant: no significant spatial clustering. Statistical significance was set at $\alpha = 0.05$, using 999 conditional permutations.

3. Results

3.1 Overall Incidence and Regional Distribution

Between 2003 and 2022, a total of 2,329,463 food poisoning cases were reported through the national surveillance system, yielding a cumulative incidence rate of 180.75 per 100,000 population. The highest annual incidence rates were recorded in 2004, 2005, and 2006 (three consecutive years). At the regional level, the northeastern and northern regions consistently recorded the highest incidence rates, followed by the central, eastern, and southern regions. The southern region consistently demonstrated the lowest incidence. At the provincial level, Ubon Ratchathani province recorded the highest cumulative mean incidence rate, while Narathiwat province recorded the lowest (Figure 1).

Analysis by five-year intervals revealed spatial evolution of high-burden areas. During 2003–2007, very high incidence (> 252 per 100,000) was concentrated across most northeastern provinces (with the exception of Maha Sarakham, Sakon

Nakhon, and Nong Khai). During 2008–2012, high incidence expanded into northern provinces while remaining elevated in the northeast. In 2013–2017 and 2018–2022, high and very high incidence persisted predominantly in the northeast and selected northern provinces, with some reduction in absolute rates relative to the early study period (Figure 2). Using the quartile stratification, the very high incidence stratum (> 252 per 100,000) over the full 20-year period encompassed provinces predominantly in the northeast (Ubon Ratchathani, Si Sa Ket, Buriram, Amnat Charoen, Nakhon Phanom, Khon Kaen, Udon Thani, and Nong Bua Lam Phu) and north (Mae Hong Son, Chiang Rai, Lamphun, Lampang, and Phayao). The low incidence stratum (≤ 93 per 100,000) was concentrated in southern provinces.

3.2 Global Spatial Autocorrelation

Global Moran's I statistics for each year are presented in Table 1. The coefficient ranged from 0.317 (2003) to 0.522 (2012) and was statistically significant ($p < 0.05$) throughout the study period, providing consistent evidence of positive spatial autocorrelation that is, provinces with similar incidence rates tended to be geographically clustered. This finding refutes the null hypothesis of random spatial distribution for all 20 study years. Table 1 presents the annual Moran' s I values alongside the number of provinces classified into each LISA cluster category.

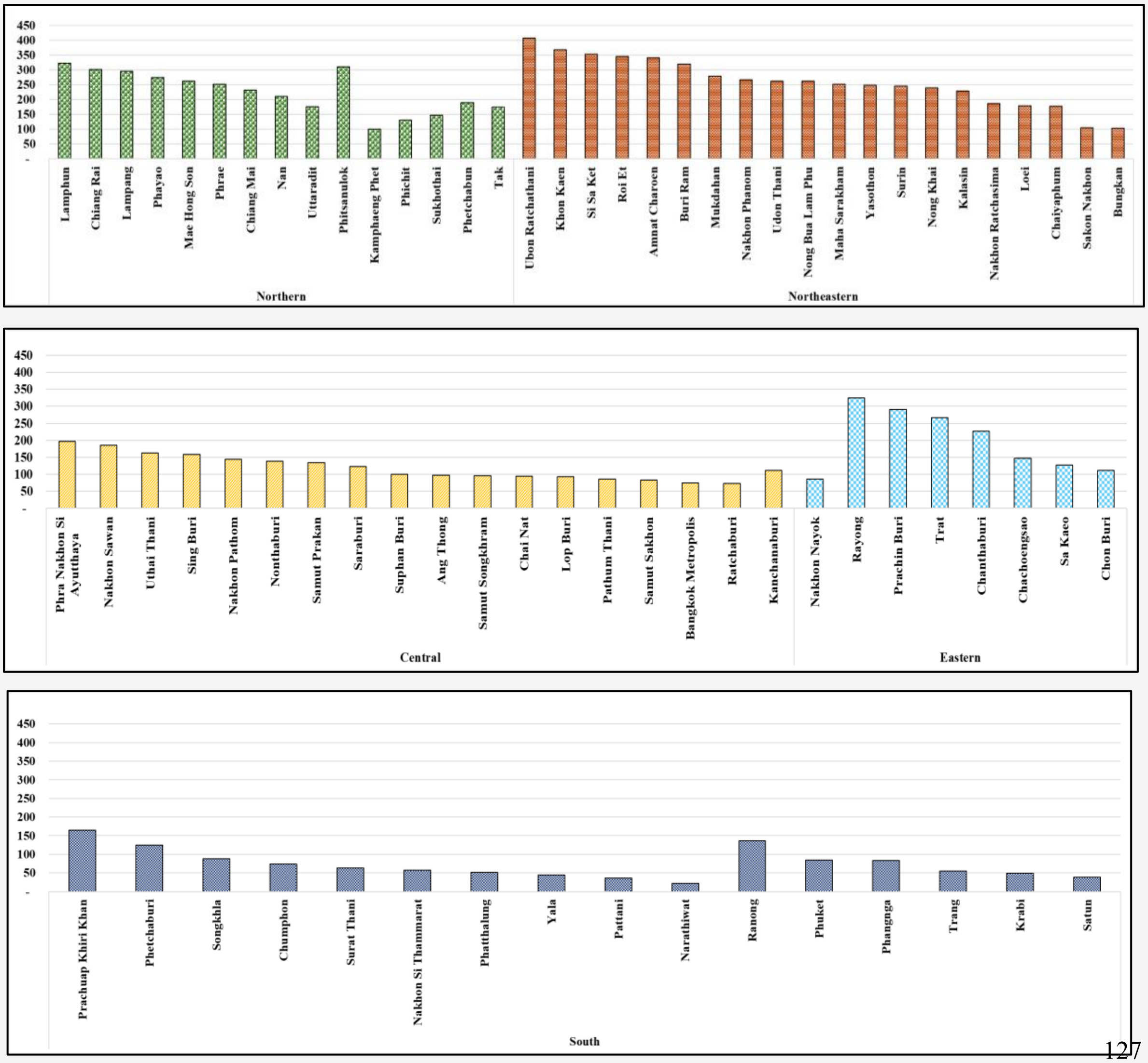

Figure 1: Food poisoning incidence rate per 100,000 population by provinces of Thailand, 2003-2022

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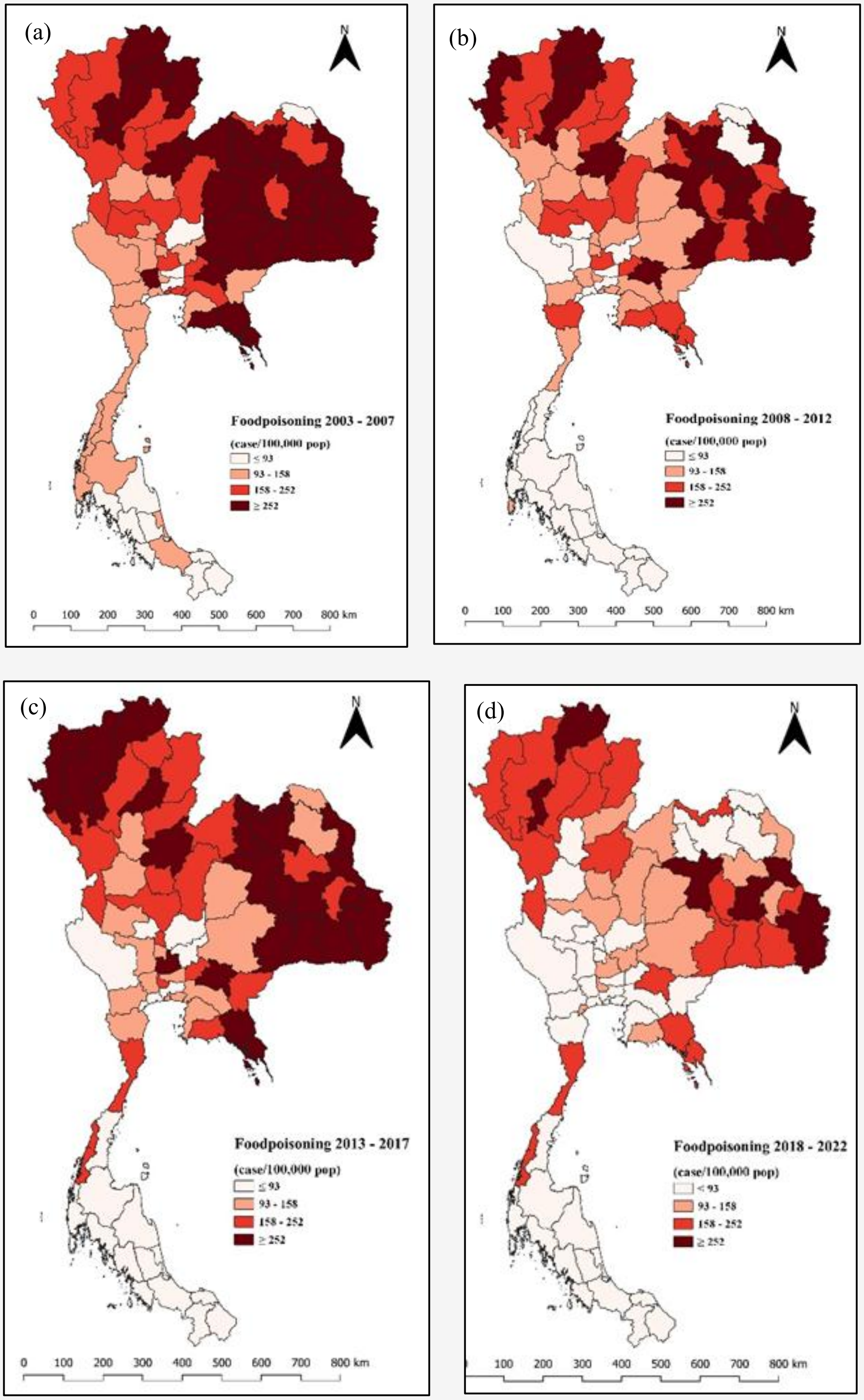

Figure 2: Spatiotemporal distribution of food poisoning incidence rate per 100,000 population by provinces of Thailand at five-year intervals:
(a) 2003-2007, (b) 2008-2012, (c) 2013-2017, and (d) 2018-2022

Table 1: Global Moran's I and LISA cluster classification of food poisoning incidence across 77 provinces of Thailand, 2003–2022

Year	Moran's I	HH*	LL*	LH	HL	Non-significant
2003	0.317	9	12	0	2	54
2004	0.514	11	18	0	1	47
2005	0.469	8	15	0	1	53
2006	0.413	10	16	1	1	49
2007	0.440	5	18	1	0	53
2008	0.501	14	18	0	0	45
2009	0.510	12	18	3	0	44
2010	0.459	14	16	3	1	43
2011	0.503	13	18	1	1	44
2012	0.522	12	14	3	1	47
2013	0.515	9	18	5	0	45
2014	0.482	8	13	5	1	50
2015	0.476	11	13	4	1	48
2016	0.501	9	17	1	1	49
2017	0.452	9	12	2	2	52
2018	0.444	11	14	2	1	49
2019	0.488	12	14	2	0	49
2020	0.358	10	14	1	3	49
2021	0.477	13	15	1	2	46
2022	0.418	10	13	0	3	51

* Statistically significant cluster type (p < 0.05, 999 conditional permutations)

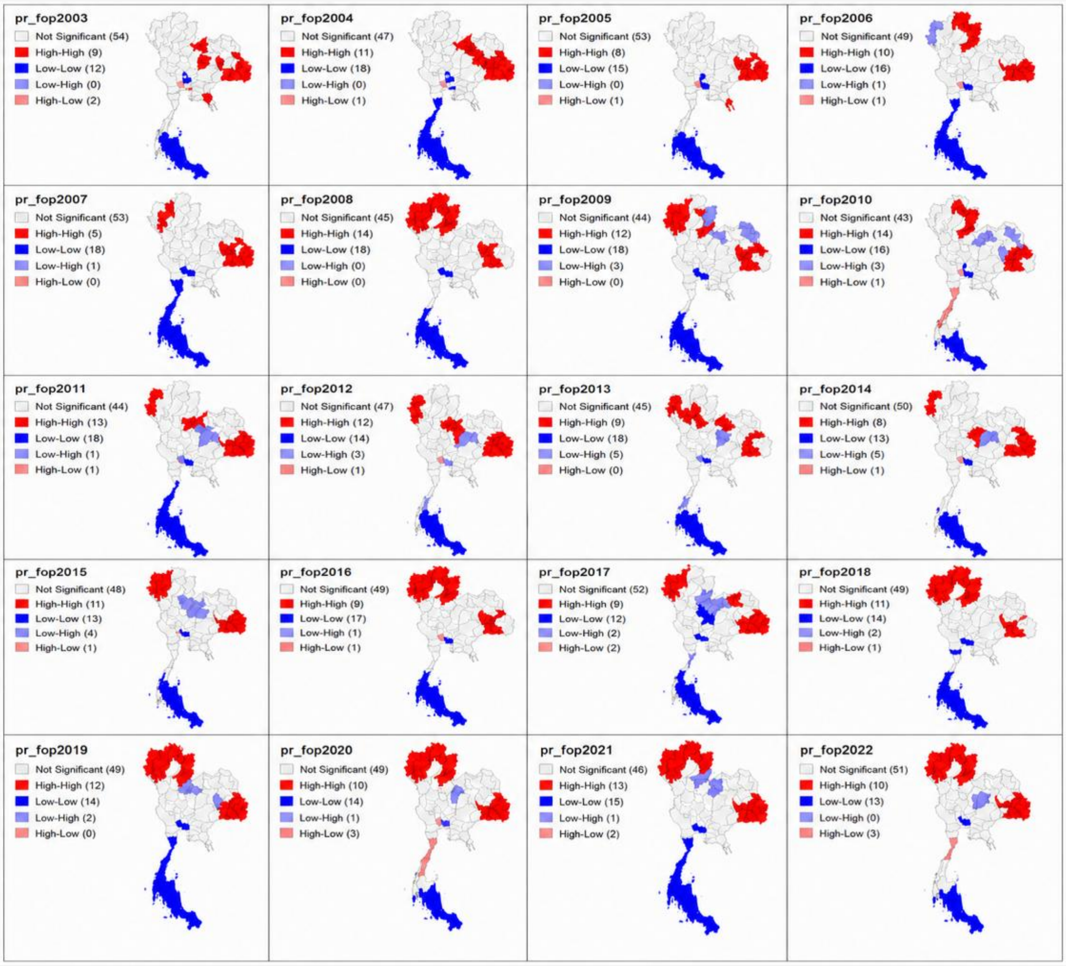

Figure 3: Spatial clustering of food poisoning at the provincial level in Thailand (2003–2022)

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3.3 Local Spatial Cluster Analysis (LISA)

High–High clusters (positive spatial autocorrelation, high incidence): The number of H–H provinces per year ranged from 5 (2007) to 14 (2008, 2010). H–H clustering was predominantly observed in the northeastern and northern regions and was consistently present from 2013 to 2022. This pattern indicates persistent high-risk spatial foci.

Low–Low clusters (positive spatial autocorrelation, low incidence): The maximum number of L–L provinces per year ranged from 12-18. L–L clustering was predominantly identified in southern provinces across nearly all study years and appeared in central provinces in 2007–2010 and 2022, reflecting persistent low-risk zones.

Low–High clusters (negative spatial autocorrelation): L–H provinces ranged from 0 to 5 per year (maximum in 2013 and 2014), representing provinces at elevated risk of disease importation from adjacent high-incidence neighbours.

High–Low clusters (negative spatial autocorrelation): H–L provinces ranged from 0 to 3 per year (maximum in 2020 and 2022), representing potential foci of disease exportation to lower-incidence neighbours. Non-significant provinces: Between 43 and 54 provinces per year demonstrated no statistically significant spatial clustering, indicating heterogeneous or random incidence patterns within those areas. LISA cluster maps for the full study period (Figure 1) confirm the persistent spatial structure of H–H clusters in the northeast and north, and L–L clusters in the south, with limited geographical dispersion over time.

Figure 3 presents Local Indicators of Spatial Association (LISA) cluster maps of food poisoning incidence at the provincial level in Thailand from 2003 to 2022. Red indicates High–High clusters, blue indicates Low–Low clusters, pink indicates High–Low spatial outliers, and light blue/purple indicates Low–High spatial outliers. Grey areas indicate provinces without statistically significant local spatial clustering. Statistical significance was assessed at $p < 0.05$ using 999 conditional permutations with first-order Queen contiguity spatial weights.

4. Discussion

This study provides 20-year evidence that food poisoning in Thailand exhibits statistically significant, geographically structured clustering that persists over time. The consistently positive Global Moran's I (range: 0.317–0.522, $p < 0.05$) demonstrates that provincial incidence rates are spatially dependent provinces with high incidence tend to be adjacent to similarly high-incidence provinces. This finding is consistent with the LISA method as applied to other infectious disease surveillance studies in Thailand and other low-and-middle-income country contexts [6].

The persistent H–H clustering in northeastern and northern provinces is consistent with an interplay of socioeconomic, dietary, and food-environment determinants operating at a regional level. First, macroeconomic data from the National Statistical Office indicate that the northeastern and northern regions have the lowest average monthly household income in Thailand (THB 21,172 and THB 20,610, respectively, in 2021, compared to THB 38,737 in Bangkok and vicinity) [7]. Lower income constrains access to safe, quality food sources and is associated with reduced food safety knowledge and unsafe food handling practices [8] and [9]. The National Economic and Social Development Council's 2024 poverty report further confirms that these regions maintain agricultural-based economies with higher poverty vulnerability [10].

Second, region-specific dietary behaviours constitute a plausible contextual risk factor. The consumption of raw or semi-cooked meat, fermented fish products (pla-ra), and traditional fermented foods is well documented in northern and northeastern Thailand. In the north, raw pork and raw pork blood consumption is associated with Streptococcus suis infection (known locally as 'hoo dub fever'), and microbial contamination of pork products sold in traditional fresh markets has been demonstrated [11][12][13] and [14]. In the northeast, pla-ra and fermented freshwater fish products show significant microbiological variability and have been reported to harbour Escherichia coli, Salmonella, Bacillus cereus, Clostridium perfringens, and Staphylococcus aureus [15][16] and [17].

The regional food environment likely represents an additional structural determinant contributing to the persistence of spatial autocorrelation. Informal food systems, traditional wet markets, and street food vendors remain dominant food access channels across northern and northeastern Thailand, particularly in areas characterised by lower socioeconomic conditions. Previous studies have demonstrated that foods obtained from informal retail environments are associated with elevated risks of microbial contamination due to inadequate temperature control, limited sanitation infrastructure, and inconsistent regulatory enforcement [18][19] and [20]. Food safety investigations conducted in Thailand have similarly reported microbial contamination among products distributed through open markets, supermarkets, street-food vendors, and food stalls, including Escherichia coli contamination [21] and [22]. From a spatial epidemiological perspective, these food-environment characteristics are spatially structured rather than randomly distributed. Their geographic distribution is closely associated with regional disparities in urbanisation, poverty concentration, market infrastructure, and local dietary culture [23][24][25] and [26]. Such conditions may facilitate the persistence of localized foodborne disease transmission and reinforce geographically concentrated vulnerability patterns. Therefore, the H–H clustering identified in this study plausibly reflects the cumulative influence of interconnected socioeconomic, cultural, and environmental determinants operating within specific regional contexts.

The persistence of L–L clustering in the south across almost all study years is consistent with differences in dietary patterns (higher consumption of fully cooked foods and lower reliance on informal fermented products), better sanitation infrastructure in coastal urban centers, and lower household food insecurity indicators relative to the northeast. The L–H and H–L spatial outlier patterns, though numerically small, identify provinces that merit surveillance attention for cross-boundary disease transmission dynamics. Importantly, these spatial patterns warrant interpretation within the framework of sustainable development. The geographic concentration of food poisoning incidence in specific regions reflects underlying structural disparities in access to safe food systems, public health infrastructure, and medical resources disparities that are closely aligned with several of the United Nations Sustainable Development Goals (SDGs). Most notably, the present findings bear direct relevance to SDG 3 (Good Health and Well-being), which seeks to reduce the burden of communicable and foodborne diseases, and SDG 10 (Reduced Inequalities), which addresses systemic disparities in health outcomes across populations and geographic units [27]. The spatial clustering identified in this study indicates that progress toward these global targets may be geographically uneven, with certain subnational regions lagging considerably behind national averages.

From a geospatial policy perspective, the integration of spatial analysis with SDG monitoring frameworks offers a substantive opportunity to strengthen evidence-based decision-making at both national and subnational levels. Spatial cluster detection methodologies can facilitate the systematic identification of priority areas where public health interventions are most urgently required, thereby enhancing the efficiency and equity of resource allocation [28]. In particular, provinces in the northeastern and northern regions that were consistently identified as High–High spatial clusters represent critical intervention zones warranting intensified epidemiological surveillance, targeted infrastructure investment, and coordinated public health programming [29] and [30]. Such place-based, geographically differentiated approaches are consistent with the foundational SDG principle of "leaving no one behind," which calls for the reduction of persistent inequalities across all dimensions of human development, including geographic disparities in health outcomes [27].

These findings extend the geographic epidemiology literature on food poisoning in Thailand. Prior spatial analysis has been applied to dengue [6] and other vector-borne diseases, but comprehensive provincial-level LISA analysis of food poisoning over a two-decade period represents a novel contribution. The results align with the broader theoretical framework of spatial epidemiology, wherein geographic clustering of disease risk reflects shared environmental, social, and behavioral exposures at a sub-national scale [31] and [32].

Several limitations should be acknowledged. First, underreporting in the Report 506 passive surveillance system is inherent and may systematically differ across regions, potentially introducing ascertainment bias into spatial estimates. Second, ecological fallacy limits causal inference from provincial-level data to individual-level risk. Third, spatial analysis was conducted at the province level; finer geographic resolution (district or sub-district) may reveal additional cluster structure. Fourth, potential confounders including temperature, precipitation, urbanization, and tourism intensity were not incorporated in the present analysis and represent important directions for future modelling.

5. Conclusions

Food poisoning in Thailand demonstrates statistically significant, positive spatial autocorrelation at the provincial level across all 20 years of surveillance data (2003–2022), with Global Moran's I ranging from 0.317 to 0.522. LISA analysis identifies persistent High–High clusters in the northeastern and northern regions and Low–Low clusters in the southern region. These spatially stable patterns are attributable to converging socioeconomic inequalities, traditional raw-food consumption behaviors, fermented food production practices, and informal food market structures. The findings provide spatial evidence base for geographically targeted food poisoning surveillance

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intensification, province-specific food safety intervention, and health promotion in cluster-identified areas, particularly in the northeast and north of Thailand.

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