Spatial Association and Modeling of Infant Mortality in Thailand, 2020

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Abstract

Infant mortality remains a pressing public health challenge globally. Despite advancements in healthcare, glaring disparities persist, as exemplified in Thailand. This study explored spatial variations in infant mortality rates (IMRs) across Thai provinces, integrating socio-economic, demographic, and health factors. Using data from national databases, we employed univariate and bivariate Local Indicators of Spatial Association (LISA) analyses to visualize spatial disparities, and Moran's I statistic assessed global spatial autocorrelation. Spatial regression models, including Ordinary Least Squares (OLS), Spatial Lag Model (SLM), and Spatial Error Model (SEM), analyzed the associations between IMRs and determinants. Our findings revealed stark IMRs disparities, especially in provinces like Phitsanulok, Narathiwat, and Songkhla. The SEM emerged as the most fitting model, given the data's spatial autocorrelation (R-Squared = 0.46). Crucial factors such as community organization strength, nighttime light, and exclusive breastfeeding were significantly linked to IMRs. Additionally, provinces like Phra Nakhon Si Ayutthaya and Rayong underscored socio-economic challenges, emphasizing the importance of tailored interventions. This study offers valuable insights for crafting targeted strategies, underscoring the pivotal role of geospatial techniques in shaping public health policies in Thailand.

Keywords: GIS, Health Disparities, HealthGIS, Infant Mortality, Spatial Analysis, Spatial Econometric Models

1. Introduction

The persistent challenge of infant mortality, characterized by the death of children before reaching their first birthday, is a grave global public health concern. This issue's ramifications aren't limited to the immediate bereaved families; they penetrate the broader socioeconomic structure of societies and shape the developmental pathways of nations. While international efforts have led to marked reductions in infant mortality rates (IMRs), closer scrutiny reveals pronounced disparities. Such differences aren't limited to global perspectives; they also persist within countries, a notable example being Thailand. Although Thailand has significantly enhanced its healthcare accessibility and quality, regional IMRs disparities remain a concern [1].

The IMRs variations across Thailand's regions are systematic and interpretable. The evident spatial distribution patterns underscore the importance of geospatial analysis in public health. Recognizing these patterns helps pinpoint 'hotspots'—regions with elevated IMRs—and elucidate the intricate mix of social, economic, and health factors that generate such disparities. This understanding optimizes resource allocation and allows for the formulation of tailored health policies, ultimately diminishing infant mortality [2]. Our study delves into the spatial patterns and IMRs determinants in Thailand for the year 2020. Building on previous research and employing spatial analysis techniques like Geographic Information Systems (GIS) and spatial econometric models, we aim to highlight IMRs geographic disparities. Moving beyond mere mapping to model and comprehend these patterns' root causes, this research hopes to shed light on regional infant mortality disparities.

Employing these nuanced analytical methods promises to yield transformative insights, indispensable for academic pursuits and policy framing.

Recognizing spatial variations has profound implications for domains like public health, policy-making, and resource distribution [3]. Aligned with the United Nations Sustainable Development Goals (SDG) for 2030, particularly SDG 3.2, this research seeks to enrich the ongoing discourse on infant mortality. This goal, targeting a neonatal mortality reduction to 12 per 1,000 live births and under-5 mortality to 25 per 1,000 by 2030, retains its global urgency [4]. The Thai government, in line with these global aims, has actively pursued initiatives to reduce infant mortality. The nation's IMRs fell from 7.6 in 2005 to 5.1 in 2020, marking significant progress. [5]. However, amidst a declining birth rate and neonatal disorders' enduring challenges, intensifying efforts to slash IMRs remains imperative [5].

In essence, this manuscript aims to demystify Thailand's IMRs spatial disparities and offer empirical insights to craft impactful interventions. By pinpointing geographic 'hotspots' and discerning these variations' primary causes, we hope to establish a solid base for policy initiatives, thereby aiding the broader mission of curtailing infant mortality.

2. Materials and Methods

After receiving approval from the Khon Kaen University Ethics Committee (reference no. 660201.2.3/362 Project ID HE652278) in Khon Kaen, Thailand, this study was conducted.

2.1 Methods

The methodology of this study was underpinned by a desire to comprehend, in depth, the spatial variations in IMRs across Thailand. Our approach was bifurcated into the use of GIS and specific spatial econometric models.

2.1.1 GIS

GIS offers a platform to capture, store, manipulate, analyze, manage, and present all types of geographical data. For this study, we specifically employed:

- Data Integration: Our primary step involved the integration of different data sources like health datasets, environmental satellite data, and socioeconomic indicators into a unified GIS database.
- Geocoding: To ensure spatial accuracy, locations were converted into geographical coordinates, mapping each data point to its precise location in Thailand.
- Spatial Visualization: We utilized thematic mapping to visualize the spatial distribution of IMRs across different provinces.

2.1.2 Spatial econometric models

Spatial econometrics provides tools to understand and interpret spatial relationships and patterns. For our study:

- Ordinary Least Squares (OLS) Estimation: Initially, the OLS model served as a foundational step to understand the linear relationships between IMRs and its potential determinants without considering spatial factors.
- Spatial Lag Model (SLM): This model was chosen to determine if the IMRs in one province could be influenced by its neighboring provinces. It accounts for spatial autocorrelation in the dependent variable.
- Spatial Error Model (SEM): SEM helped us examine if there were any unaccounted spatial effects in the model residuals, ensuring the error term is not spatially autocorrelated.

2.2 Data Collection

Secondary data for this study were meticulously sourced from a range of dependable institutions to ensure a comprehensive understanding of the factors underpinning IMRs in Thailand for the year 2020.

- Health Metrics: Data pertaining to IMRs per 1,000 live births, low birth weight (defined as a birth weight less than 2,500 grams), the number of nurses per 1,000 population, and exclusive breastfeeding rates (defined as the practice of feeding an infant only breast milk for the first 6 months, without any supplemental liquids or solids except for vitamins, mineral supplementation, or medications) were obtained from the Ministry of Public Health.
- Socioeconomic Indicators: From the Office of the National Economic and Social Development Council, we sourced statistic on the community organizations. In this context, community organizations refer to certified groups established by community members with explicit systems of governance to collaboratively pursue objectives related to occupational advancement, income growth, habitat and environmental improvement, or overall quality of life enhancement. These organizations possess distinct organizational rules, management systems, elected committees, and continuous development plans, and are recognized by local certification mechanisms. The data used pertains to cumulative information on certified community organizations.

- Nighttime Light (NTL): Data for nighttime luminosity in 2017 was sourced from the National Centers for Environmental Information (NCEI). The data represents artificial light emissions captured by the NPP/VIIRS satellite between 20:30 to 22:00 hrs. The measurements of this light are presented in the unit of nW/cm^2/sr. The term 'Digital Number' (DN) is used to denote the numerical value of each pixel in the dataset. While DN signifies the brightness of each pixel, it's crucial to note that DN is not the unit of measure; it's merely a numerical representation. For our data, higher DN values correspond to brighter light and vice versa. A DN value of zero indicates no light was detected. For the purpose of our analysis, we determined the average nighttime light intensity for each province. This was achieved by computing the mean value of the pixels (in nW/cm^2/sr) within the boundaries of each province using the zonal statistic method. The conversion of this data from raster to vector format facilitated this provincial-level assessment. Nighttime light serves as a proxy for several indicators such as urban expansion, energy consumption, and economic activity. Such indicators can indirectly impact Infant Mortality Rates (IMRs) by influencing factors like living conditions, healthcare access, and economic stability within households. More details can be found on the VIIRS website (https://ncc.nesdis.noaa.gov/ VIIRS/) and the Earth Observation Group (https://eogdata.mines.edu/products/vnl/).

- Agricultural Land Use: The Office of Agricultural Economics supplied data on the proportion of land earmarked for agricultural activities. Land use broadly signifies how land is utilized for various human needs. An increased proportion of agricultural land use might correlate with certain socioeconomic conditions or health outcomes, particularly in areas where agriculture is the predominant means of livelihood. For this research, the data from 2019 was particularly considered, as outlined in the Office of Agricultural Economics' 2020 report.

- Healthcare Infrastructure: The National Statistical Office provided statistic on the number of beds available for inpatients per 1,000 population.

The integration of these specific variables was inspired by a comprehensive review of existing literature. Key studies suggested the pertinence of these factors in understanding regional variances in IMRs, thus driving our selection of these 7 primary determinants. As such, our selection, ranging from healthcare metrics to socioeconomic indicators and environmental variables, formed a robust foundation for our analysis.

2.3 Spatial Analysis

Spatial analysis was conducted using GIS tools: GeoDa^{TM} version 1.18.0 (10 December 2020), which facilitated the visualization of IMRs across different provinces of Thailand. These visualizations allowed us to discern initial patterns and potential clusters of high IMRs. The GIS maps were created using a color-coded system to represent variations in IMRs across the country.

2.4 Spatial Autocorrelation

To measure the spatial autocorrelation of infant mortality rates, we used the Global and Local Moran's *I* statistics. These statistical tools help detect whether the distribution of infant mortality is random across the country or if there are certain geographic areas were high or low rates cluster together. A significant positive Global Moran's *I* would suggest that provinces with similar infant mortality rates are geographically close to each other, indicating a spatial clustering of high and low rates. The formulas for Global and Local Moran's *I* are as follows:

Global Moran's *I* is calculated using the following (Equation 1):

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i-\bar{x}\right)\left(x_j-\bar{x}\right)}{\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2}$$

Equation 1

Local Moran's *I*, on the other hand, is computed as follows (Equation 2):

$$I_i = \frac{\left(x_i-\bar{x}\right)}{s}\sum_{j=1}^{n} w_{ij}\frac{\left(x_j-\bar{x}\right)}{s}$$

Equation 2

where:

n is total number of regions

x_i and x_j are attribute values for the spatial units i and j

$\bar{x}$ is mean of the attribute across all spatial units

w_{ij} is spatial weight between spatial unit i and spatial unit j. It represents the spatial relationship between i and j

while *s* is the standard deviation of the attribute [6] and [7]. In this study, the spatial autocorrelation was gauged via Local Indicators of Spatial Association (LISA), an ensemble of statistics that encapsulates numerous metrics for pinpointing various spatial configurations, inclusive of the well-known Moran's *I*. To appraise the global spatial autocorrelation concerning IMRs and its linked factors, LISA came into play.

More pointedly, we employed Moran's *I* a metric housed within LISA to discern if specific regions belonged to spatial groupings of matching or contrasting IMRs values, such as clusters of High-High (HH) or Low-Low (LL). Additionally, this metric was instrumental in detecting outliers, which can be categorized as High-Low or Low-High clusters. Such an approach granted us the capability to visually grasp spatial inconsistencies and highlight probable clusters or focal areas at a granular scale.

2.5 Spatial Econometric Models

After detecting the presence of spatial autocorrelation, our methodology hinged on the deployment of spatial econometric models. The formulas for OLS, SLM, and SEM are presented in Equations 3, 4, and 5 respectively:

$$Y = B_0 + B_1 X + \varepsilon$$

Equation 3

$$Y = \rho WY + X\beta + \varepsilon$$

Equation 4

$$Y = X\beta + \lambda W_\varepsilon + \varepsilon$$

Equation 5

where:

Y is dependent variable
X is matrix of independent variables
β is vector of coefficients
ε is error term
ρ is spatial autoregressive parameter
WY is spatially lagged dependent variable (spatial multiplier effect)
λ is spatial error coefficient
$W\varepsilon$ is patially autocorrelated error

The OLS Estimation functions as the basic method, providing a fundamental understanding of the relationships between variables. Its simplicity stands as its strength, ensuring ease of understanding and implementation. Nevertheless, in spatial analyses, OLS may be inefficient when confronted with spatial autocorrelation because it doesn't inherently factor in spatial structures in the data. To integrate the influence of neighboring regions, we employed the SLM. This was to determine if the IMRs in a specific province was influenced by the rates observed in its neighboring provinces. Central in analyzing spatial spillover effects, this model addresses spatial autocorrelation directly in the dependent variable. It does, however, operate under the assumption that the observed spatial autocorrelation mainly stems from the dependent variable. Contrastingly, the SEM delves into whether the error term, or the unaccounted-for variance, manifests spatial autocorrelation. By spotlighting the error term, SEM encapsulates spatial patterns in unobserved influences. It's a robust model for spatially autocorrelated errors, though it may not always capture potential spatial spillover effects in the dependent variable.

To refine our models and potentially bolster their explanatory power, we considered employing a stepwise forward approach. This approach systematically introduces independent variables into the model, permitting only those that contribute significantly to its fit. This can aid in removing non-significant independent variables, thereby striving for a model exhibiting maximal fitness. The model assessment involves several critical metrics to gauge the goodness-of-fit: Log-Likelihood, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). A model with a higher Log-Likelihood value suggests a superior fit. Concurrently, both AIC and BIC serve to strike a balance between the model's precision and its complexity, with lower values indicating a more desirable fit while maintaining model parsimony. An integral aspect of our assessment for spatial models is the consideration of the Residual Moran's *I*, which measures spatial autocorrelation in the model's residuals. This metric becomes pivotal in spatial econometric models:

- In the OLS model, the Residual Moran's *I* will indicate if there's a need to account for spatial effects.
- For the SLM, a significant Residual Moran's *I* would suggest that neighboring regions have an influence on the infant mortality rate of a particular region.
- For the SEM, the Residual Moran's *I* would help us detect spatial autocorrelation in the error terms.
- A Residual Moran's *I* value closer to zero would imply that the model has effectively accounted for spatial patterns, indicating that residuals are more randomly distributed spatially.

By integrating these statistical and spatial analysis tools, we aim to provide a comprehensive exploration of the variables that determine the spatial disparities in IMRs across Thailand. This combined methodology is designed to yield a nuanced view of the spatial distribution of IMRs, shedding light on potential 'hotspots' and the significant determinants of observed patterns. All statistical analyses will be conducted with a significance level set at α = 0.05, unless otherwise specified. The study workflow is illustrated in Figure 1.

3. Results and Discussion

Understanding the intricacies of IMRs across provinces offers essential insights into healthcare access, socio-economic factors, and overall well-being in regions. Our analysis, conducted against the backdrop of 569,338 births in Thailand, 2020, elucidates these intricate dynamics.

3.1 Spatial Distribution

Utilizing GIS mapping, as shown in Figure 2, a pronounced disparity in IMRs across various provinces became evident. Specifically, Phitsanulok, Narathiwat, Songkhla, Trang, Rayong, Phuket, Khon Kaen, Ranong, Mae Hong Son, and Phra Nakhon Si Ayutthaya emerge as the top 10 provinces with the highest IMRs. The disparities observed in IMRs across provinces point towards a need for targeted policy initiatives, ensuring resource allocation is commensurate with provincial demands.

3.2 Spatial Autocorrelation

3.2.1 Global spatial patterns

As illustrated in Figure 3, the Global Moran's *I* statistic produced a value of 0.175, indicative of positive spatial autocorrelation. It's critical, however, to recognize that the mere value of Global Moran's *I* in isolation doesn't definitively attest to the presence or absence of spatial clusters. For a comprehensive assessment of the non-random distribution of IMRs across provinces, the *p*-value associated with this statistic is equally imperative. A noteworthy aspect of the Global Moran's *I* values is that while positive values typically signify similarity between neighboring areas, negative values can still denote clustering, but of contrasting values.

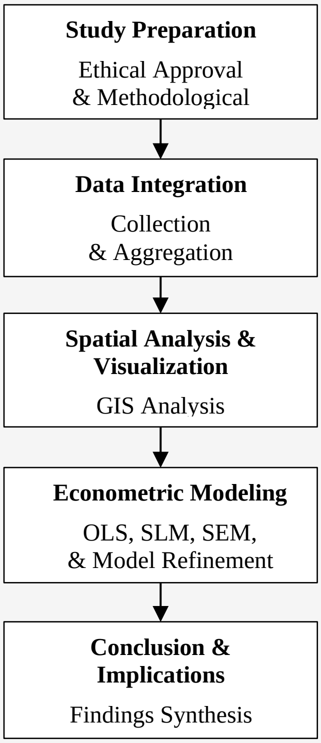


Figure 1: Workflow diagram of the methodology

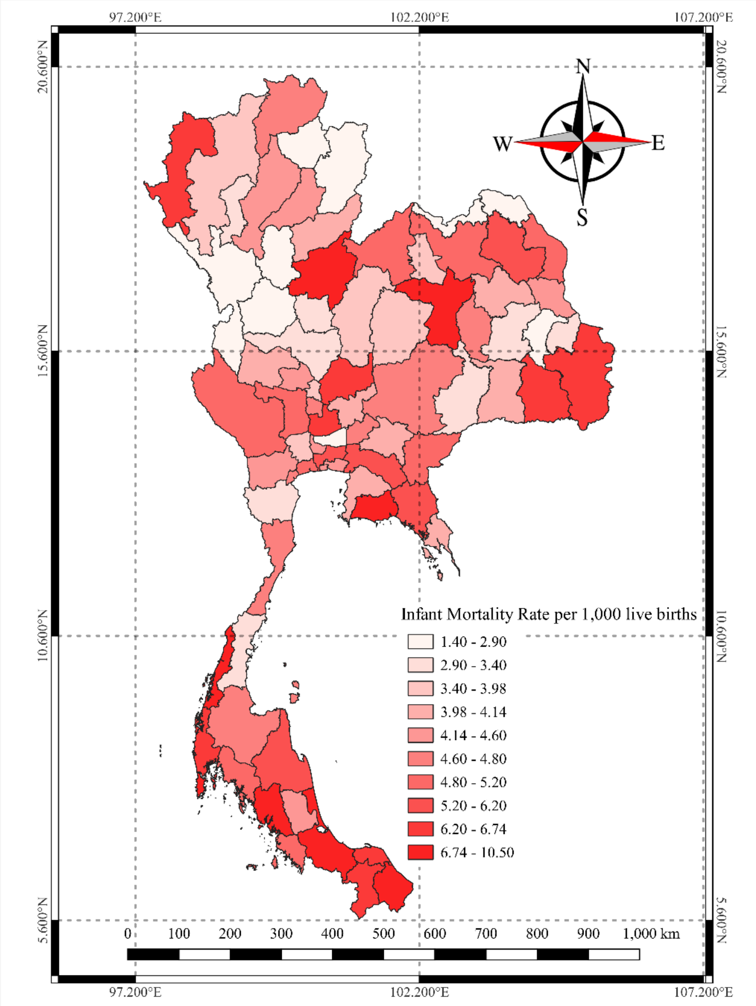
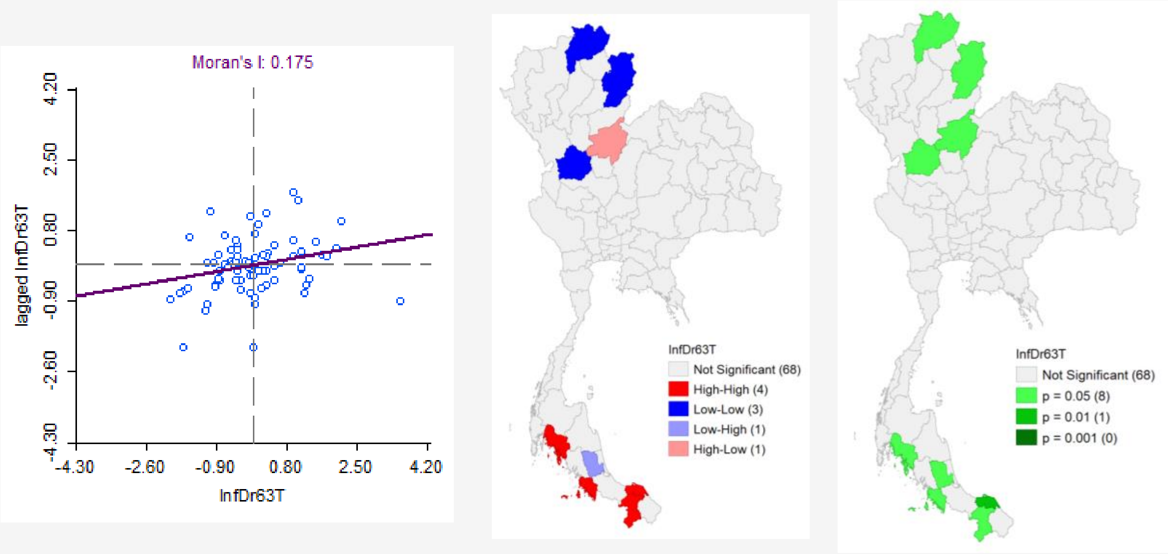


Figure 2: Infant mortality rate per 1,000 live births in Thailand, 2020



(a) (b) (c)

Figure 3: Univariate spatial correlation of infant mortality rate,
(a) Global Moran's *I* scatter plot (b) Infant mortality clusters (c) LISA *p*-value

3.2.2 LISA

Using the LISA method, we discerned distinct local spatial patterns. These analyses spotlighted HH clusters of infant mortality in southern-region provinces such as Krabi, Pattani, Yala, and Satun, while identifying LL clusters in northern-region provinces like Chiang Rai, Nan, and Kamphaeng Phet. Intriguingly, Pattalung presented a Low-High pattern, and Phitsanulok exhibited a High-Low dynamic. These local correlations were statistically significant, mostly at the 0.05 level, with Pattani being an outlier at a stringent 0.01 level of significance.

3.2.3 Bivariate spatial relationships

As portrayed in Figure 4, we employed a bivariate analysis using Moran's I and LISA to illuminate the spatial interplay between various influential factors and infant mortality rates across Thai regions.

- Moran's I Analysis: Factors such as low birth weight (0.197), the proportion of land used for agricultural purposes (0.121) and number of nurses per 1,000 population (0.079) exhibited robust positive spatial autocorrelation with infant mortality. This suggests a concerning trend wherein regions with high values for these factors also face elevated IMRs. In contrast, factors like community organizations (-0.087) and exclusive breastfeeding (-0.101) demonstrated negative spatial autocorrelation, suggesting these factors might be protective against high IMRs. Some factors, like NTL (0.049) and number of beds for inpatients per 1,000 population (0.007), showed more subdued correlations, implying their effects might be indirect or less pronounced in the Thai context.
- LISA Analysis: On a granular level, LISA unearthed regional specificities. Predominantly, southern Thailand manifested a concerning synergy of high values for influential factors with elevated IMRs. Conversely, the northern regions presented a more reassuring pattern, with lower influential factor values corresponding with decreased IMRs.

This intricate, dual-faceted analysis, weaving together overarching spatial trends with localized insights, offers an exhaustive landscape of the myriad dynamics between different determinants and infant mortality in Thailand. These findings, grounded in robust statistical techniques, provide a foundational blueprint for strategizing targeted interventions to address infant mortality in Thailand's diverse regions.

3.3 Spatial Regression Models

Our inquiry into the spatial distribution of IMRs and their relationships with distinct determinants utilized three regression models: OLS, SLM, and SEM. Detailed outcomes from these analyses are tabulated in Table 1.

- Low Birth Weight: Across all models, this determinant exhibited a positive association with IMRs. Notably, it was statistically significant in the SLM and SEM frameworks (p-value < 0.05).
- Community Organizations: All models consistently highlighted a negative relationship between community organizations and IMRs. This association was especially robust, with a significance level of p-value < 0.001.
- Nighttime Light: While showcasing a negative correlation with IMRs, its most significant relationship was evident in the SEM model (p-value < 0.05).
- Healthcare Infrastructure: Two critical healthcare metrics - the number of nurses and inpatient beds per 1,000 population - surfaced as significant determinants. The former exhibited a positive relationship with IMRs, significant at p-value < 0.01, while the latter demonstrated a protective negative relationship, significant at p-value < 0.05.
- Exclusive Breastfeeding: Serving as a protective factor, exclusive breastfeeding consistently portrayed a negative relationship with IMRs. Its most significant association was evident within the SLM framework (p-value < 0.001).

In evaluating the model fits, the SEM outperformed both OLS and SLM. This superiority is evident through its highest Log Likelihood values and the lowest AIC and BIC metrics. Delving into the residuals, Moran's I values for OLS, SLM, and SEM were recorded as -0.085, -0.092, and -0.006, respectively. This indicates the degree of spatial autocorrelation, with SEM showcasing the least. Significantly, the pronounced λ in the SEM (p-value < 0.001) reinforces the relevance of spatial relationships within our dataset.

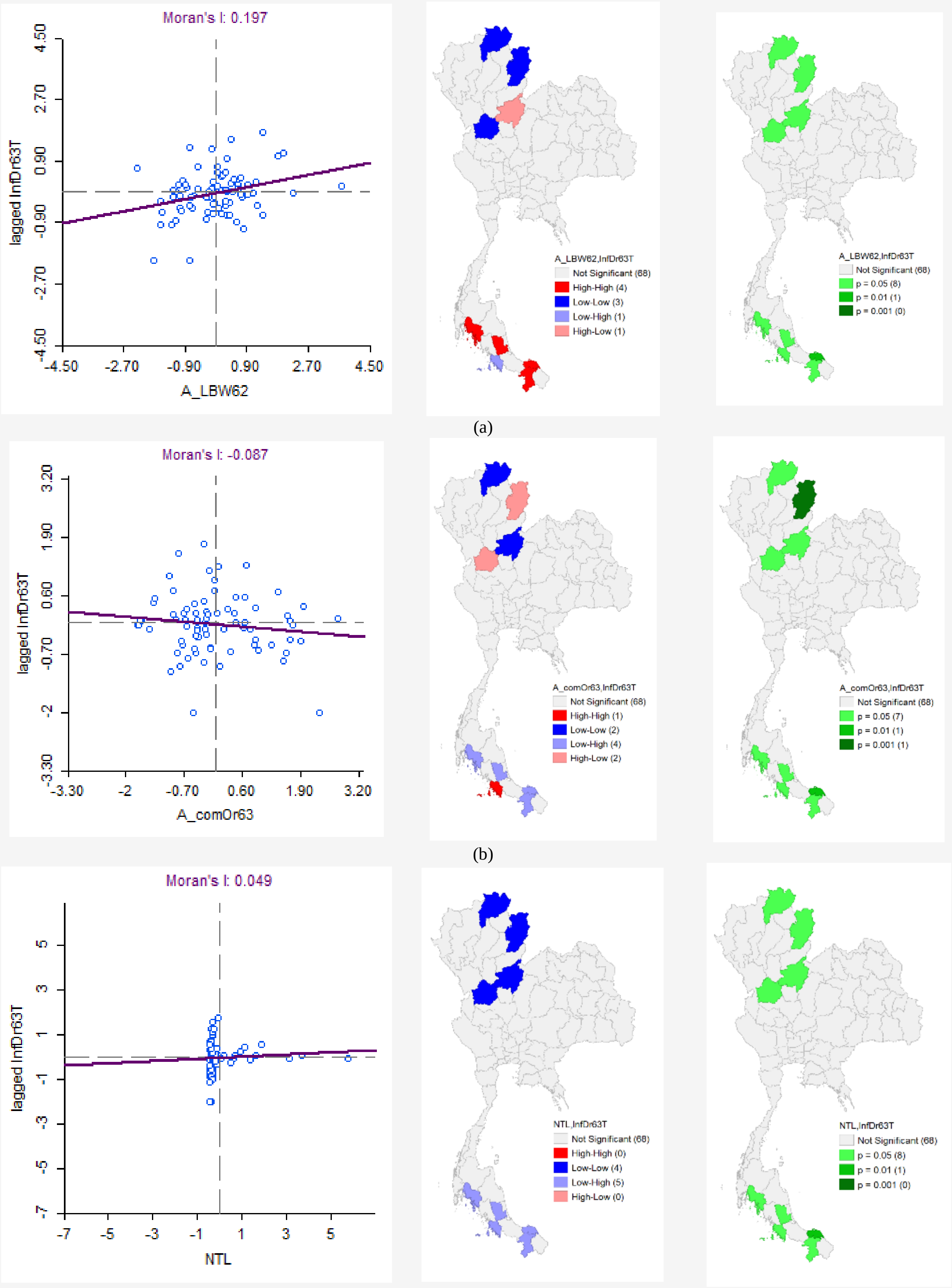
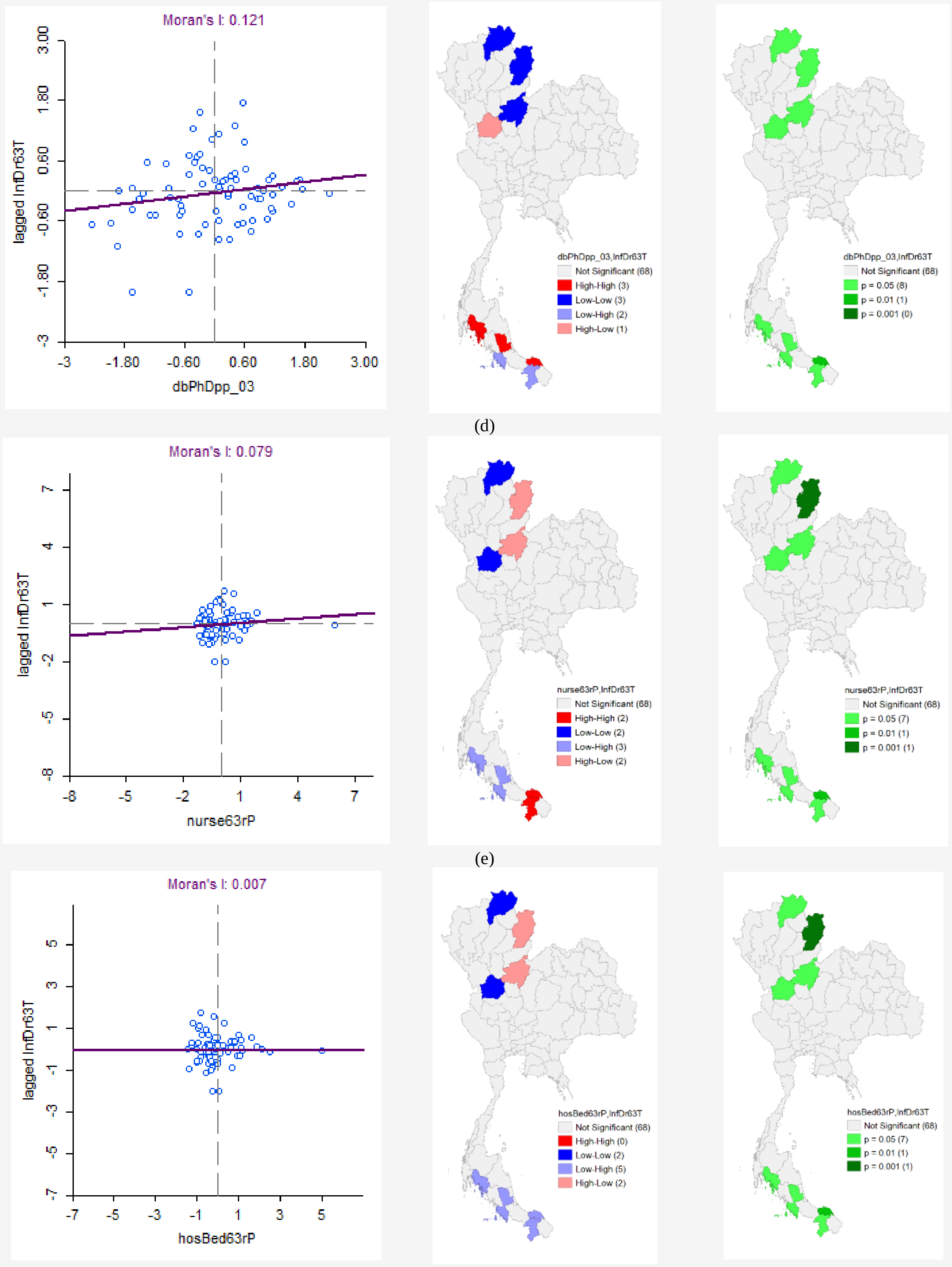


Figure 4: Bivariate spatial correlation between influencing factors and infant mortality rate, as (a) Low birth weight (b) Community organizations (c) Nighttime Light (continued to next page)

Left: Global Moran's *I* scatter plot. Middle: Infant mortality clusters. Right: LISA *p*-value



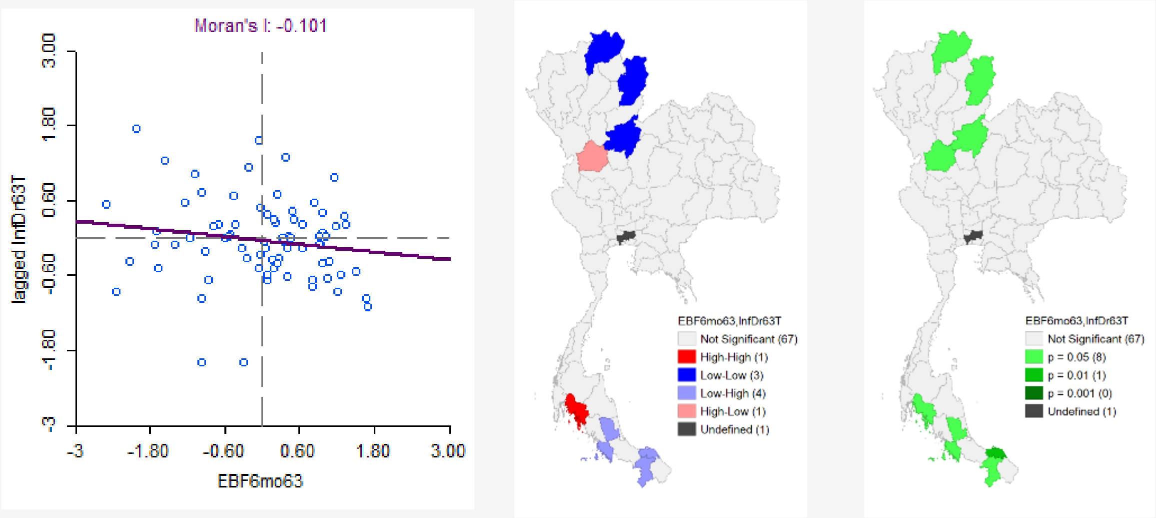
(d)

(e)

(f)

Figure 4: Bivariate spatial correlation between influencing factors and infant mortality rate, as (d) Proportion of land used for agricultural purposes (e) Number of nurses per 1,000 population, (f) Number of beds for inpatients per 1,000 population (continued to next page)

Left: Global Moran's *I* scatter plot. Middle: Infant mortality clusters. Right: LISA *p*-value



(g)

Figure 4: Bivariate spatial correlation between influencing factors and infant mortality rate, as (g) Exclusive breastfeeding, (continued from previous page)

Left: Global Moran's *I* scatter plot. Middle: Infant mortality clusters. Right: LISA *p*-value

Table 1: Spatial regression model that has an impact on infant mortality rates

Factors	OLS Coefficient (SE)	Spatial Regression Analysis	
		SLM Coefficient (SE)	SEM Coefficient (SE)
Low Birth Weight (Percentages)	0.39 (0.20)	0.38 (0.19)*	0.44 (0.18)*
Community Organizations (per 1,000 Populations)	-0.42 (0.11)***	-0.42 (0.11)***	-0.42 (0.11)***
Nighttime Light (nW/cm^2/sr)	-0.13 (0.08)	-0.13 (0.07)	-0.14 (0.07)*
Proportion of land used for agricultural purposes (Percentages)	0.94 (0.81)	0.92 (0.77)	1.19 (0.72)
Number of nurses per 1,000 population (Rate)	1.50 (0.48)**	1.49 (0.46)**	1.50 (0.43)***
Number of beds for inpatients per 1,000 population (Rate)	-1.24 (0.55)*	-1.22 (0.54)*	-1.19 (0.5)*
Exclusive breastfeeding (Percentages)	-0.04 (0.01)**	-0.04 (0.01)***	-0.04 (0.01)***
Constant	3.66 (2.22)	3.63 (2.15)	3.05 (2.05)
ρ		0.02	
λ			-0.16***
F-statistic	7.92		
R-Squared	0.45	0.45	0.46
Log Likelihood	-122.545	-122.537	-122.026
AIC	261.089	263.073	260.053
BIC	279.735	284.050	278.699

* Significance at *p*-value < 0.05; ** Significance at *p*-value < 0.01; *** Significance at *p*-value < 0.001; OLS: Ordinary Least Squares method; SLM: Spatial Lag Model; SEM: Spatial Error Model; SE: Standard Error measure; Constant: Model intercept when predictors = 0; ρ: Rho, spatial autoregressive parameter; λ: Lambda, spatial error coefficient; F-statistic: Variance comparison ratio; R-Squared: Variance proportion explained by predictors; AIC: Akaike's model fit criterion; lower is better; BIC: Bayesian model fit criterion; prefers fewer parameters.

3.4 Discussion

Our exploration into the dynamics of infant mortality in Thailand has unearthed complex determinants that shift across distinct geographical regions. Central findings include:

- A significant spatial clustering of IMRs across Thailand.
- Diverse IMRs between provinces.
- A disparity in risk factors based on urban-rural and socio-economic distinctions.

- The profound role of community involvement, breastfeeding, and healthcare accessibility on IMRs.

Using geospatial analysis techniques, we've identified regions with pronounced IMRs and systematically evaluated influential factors. This discussion addresses the wider ramifications of these findings, particularly in the realm of public health and policy recommendations.

3.4.1 Model reliability concerns

The observed positive correlation between the number of nurses per 1,000 population and IMRs in Thailand may initially appear counterintuitive. This raises concerns about the reliability of the models, especially given the R-squared of SEM being just 0.46. Addressing this issue, and the potential implications of our findings, is essential. It's imperative to note that the R-squared value indicates that almost 54% of the variability in the response variable isn't explained by the model. Moreover, when considering the fundamental equation of IMRs — the number of deaths of infants under one year of age per 1,000 live births — the sheer number of births in each province becomes a focal point. This is crucial for gauging the scale of the infant mortality challenge in different regions.

3.4.2 Spatial distribution of IMRs

Our findings indicate significant spatial clustering in IMRs across Thailand, with several provinces such as Phitsanulok, Narathiwat, and Songkhla showing notably higher rates. Provinces with elevated IMRs suggest spatial clustering, but this doesn't indicate a uniform risk. Differences can be profound between urban and rural settings and among varied socio-economic backgrounds. The granular nuances revealed by our GIS mapping mandate more detailed, region-specific investigations. Such disparities underscore the need to delve deeper and investigate the unique challenges and influencing factors present in each province.

3.4.3 Factors and their influence

- Number of Births: A vital metric not deeply explored in our study is the number of births in each province. When considering the fundamental equation of IMRs — the number of deaths of infants under one year of age per 1,000 live births — the sheer number of births in each province undeniably matters. It becomes a focal point for gauging the scale of the infant mortality challenge in different regions. This metric could provide a more nuanced understanding of regional IMR disparities in future research endeavors.
- Community Organizations: Our findings emphasize the role of community organizations in potentially reducing IMRs. These organizations augment healthcare access, especially for the underprivileged, and evidence from countries like Kenya supports this observation [8].
- Nighttime Light & Healthcare Infrastructure: Regions with higher NTL and healthcare infrastructure typically show reduced IMRs, possibly indicating better socio-economic conditions [9] and [10].
- Exclusive Breastfeeding and Low Birth Weight: Both factors play pivotal roles in influencing IMRs. Exclusive breastfeeding, recommended by the World Health Organization (WHO) for the first six months of life [11], acts as a protective factor against various infections, ensuring optimal nutrition and a bolstered immune system [12] [13] and [14]. Conversely, low birth weight poses significant risks to infant health, being associated with a plethora of complications and higher mortality rates [15] [16] [17] [18] [19] and [20]. Interventions aimed at promoting exclusive breastfeeding and reducing the incidence of low birth weight can substantially enhance infant health outcomes.
- Nurse Availability: The unexpected positive correlation between nurse availability and IMR requires further investigation. This anomaly might hint at other underlying socio-economic challenges or potential issues with healthcare resource allocation [21] [22] and [23].
- Agricultural Land: Regions with significant agricultural activity may face increased IMRs due to challenges in healthcare accessibility and socio-economic stability [24] [25] and [26].

3.4.4 Key takeaways and recommendations

- Model Specificity: While the SEM model has been identified as the best fit for our dataset, the pronounced disparities in IMRs across provinces like Phitsanulok, Narathiwat, and Songkhla emphasize the need for models tailored to specific provincial challenges. Policymakers should ensure accurate data interpretation when devising strategies to combat infant mortality in these high-risk areas.
- Socioeconomic Focus: With provinces such as Phra Nakhon Si Ayutthaya and Rayong among the top 10 provinces with the highest IMRs, there's a dire need to delve deeper into socioeconomic challenges that might be contributing to these high rates. Addressing

broader societal concerns, particularly around unemployment, poverty, and education, can make a significant difference in such regions.

- Healthcare Resources: Even though regions like Mae Hong Son and Ranong might have healthcare facilities, there is a clear need to ensure effective distribution and quality assurance. Such measures will ascertain that resources are not just abundant but also effective in improving outcomes.
- Public Health Promotion: In southern provinces like Krabi, Pattani, Yala, and Satun, which have exhibited High-High clusters of infant mortality, health initiatives promoting community involvement and exclusive breastfeeding might be particularly impactful. Tailored public health campaigns that cater to the unique cultural and societal norms of these regions can lead to tangible improvements in infant health outcomes.
- Future Research: The unique patterns observed in provinces like Pattalung (Low-High) and Phitsanulok (High-Low) suggest that there are still unexplored factors influencing IMRs in these areas. Detailed studies focusing on such specific patterns will be pivotal in understanding and addressing the nuances of IMRs in these provinces.

4. Conclusion

Our study, using GIS techniques, unraveled distinct geographical disparities in IMRs across Thailand. The significance of this technique lies in its capacity to visually capture and quantitatively analyze IMRs clusters, effectively showcasing provinces like Phitsanulok, Narathiwat, Songkhla, and Pattalung with pronounced disparities. This granularity provided by GIS techniques empowers policymakers with province-specific insights, enabling them to target interventions more efficiently. Specifically, our findings highlight provinces such as Phra Nakhon Si Ayutthaya and Rayong, which necessitate socio-economic interventions, and southern provinces like Krabi, Pattani, Yala, and Satun, where tailored public health campaigns might make a significant impact.

These province-specific insights underscore the importance of employing geospatial analytics in public health studies. Moreover, while the focus on factors such as community organizations, NTL, and exclusive breastfeeding has been instrumental in shedding light on IMRs determinants, there remains a need to delve deeper into unexplored factors, such as the number of births in each province, to offer a more comprehensive understanding. In conclusion, while our study may not revolutionize the understanding of infant mortality, it undeniably contributes to the local context, facilitating policymakers in crafting effective, targeted interventions. The role of GIS techniques in health planning and policy-making is pivotal, as evidenced by our findings, and should be emphasized in future research to continually refine interventions.

Limitations

Every scientific inquiry has its boundaries, and ours is no exception. The careful interpretation of our study findings necessitates an understanding of the inherent limitations. Firstly, the study uses an ecological design, which inherently prevents us from making causal inferences at the individual level. This limitation arises from the ecological fallacy where relationships observed for groups do not necessarily hold for individuals [27]. While we identified various factors associated with infant mortality at the provincial level, these relationships might not hold true at an individual level. Therefore, it is essential to interpret our findings in the context of the study's ecological design.

Secondly, our study was cross-sectional, using data from a single point in time. As a result, we were unable to establish a temporal relationship between our studied factors and infant mortality. Longitudinal studies would provide valuable insights into the evolution of infant mortality over time and the impact of various factors [28]. Another limitation lies in the fact that some relevant variables could not be incorporated into our analysis due to data unavailability. This includes potentially significant factors such as healthcare quality indicators, more granular socioeconomic variables, or individual health behaviors, which are known to impact health outcomes significantly [23] and [29].

Moreover, although the SEM demonstrated the best fit among the models tested, it still suggested the presence of spatially structured errors. This finding indicates that some spatially dependent variables influencing infant mortality were not captured in our model [30]. This unobserved spatial heterogeneity can lead to biased estimates, and further research should endeavor to incorporate these missing variables.

Finally, our reliance on administrative data sources, while offering substantial coverage and scope, could also limit our study's accuracy. Such datasets often lack detail on important confounding variables, have standard errors that can be challenging to estimate, and may contain inaccuracies from reporting or measurement errors [31]. Therefore, the potential for bias from our data sources cannot be overlooked.

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