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Spatial association and modelling of under-5 mortality in Thailand, 2020

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Abstract

Under-5 mortality rate (U5MR) is a key indicator of child health and overall development. In Thailand, despite significant steps made in child health, disparities in U5MR persist across different provinces. We examined various socio-economic variables, health service availability and environmental factors impacting U5MR in Thailand to model their influences through spatial analysis. Global and Local Moran's *I* statistics for spatial autocorrelation of U5MR and its related factors were used on secondary data from the Ministry of Public Health, National Centers for Environmental Information, National Statistical Office, and the Office of the National Economic and Social Development Council in Thailand. The relationships between U5MR and these factors were modelled using ordinary least squares (OLS) estimation, spatial lag model (SLM) and spatial error model (SEM). There were significant spatial disparities in U5MR across Thailand. Factors such as low birth weight, unemployment rate, and proportion of land use for agricultural purposes exhibited significant positive spatial autocorrelation, directly influencing U5MR, while average years of education, community organizations, number of beds for inpatients per 1,000 population, and exclusive breastfeeding practices acted as protective factors against U5MR (R^2 of SEM = 0.588).The findings underscore the need for comprehensive, multi-sectoral strategies to address the U5MR disparities in Thailand. Policy interventions should consider improving socio-economic conditions, healthcare quality, health accessibility, and environmental health in high U5M areas. Overall, this study provides valuable insights into the spatial distribution of U5MR and its associated factors, which highlights the need for tailored and localized health policies and interventions.

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Introduction

Childhood mortality, specifically the under-5 mortality rate (U5MR) and the neonatal (under-28) mortality rate (U28MR), are important global public health issues. The pressing need to address this matter aligns with the third Sustainable Development Goal (SDG) set by the United Nations (UN) for 2030 (UN, 2018). Target 3.2 of the SDG aspires to "Reduce avoidable death of newborns and children under the age of five", with the specific aims to reduce the U28MRto at least 12 per 1,000 live births and U5MR to at least 25 per 1,000 live births by 2030 (UN, 2018).The projection for 2030 suggests that 154 countries, which accounts for 75% of all nations worldwide will accomplish the U5MR target, and 139 countries (68%) will achieve the neonatal mortality goal (Hug *et al.*, 2019). The accomplishment of these targets will mark a significant step forward in global health outcomes and equity.

In Thailand, the milestones of SDG 3.2 were fully accomplished as early as 2002. Over the past 15 years, the country has shown a promising trend in reducing childhood mortality. According to data from its Strategy and Planning Division (2020), the U5MR (per 1,000 live births) decreased from 10.8 in 2003 to 7.0 in 2020. Similarly, the U28MR (per 1,000 live births) declined from 4.5 in 2003 to 2.9 in 2020. Moreover, the infant mortality rate (per 1,000 live births) dropped from 7.6 in 2003 to 5.1 in 2020.In 2020, Thailand reported 3,960 deaths in children under-5.

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The province with the highest U5MR was Phitsanulok with a rate of 13.50 per 1,000 live births, while Phayao had the lowest rate, at 1.40 per 1,000 live births. The provinces grouped in the highest U5MR decile (9.30 - 13.50 per 1,000 live births) included Phitsanulok, Songkhla, Narathiwat, Khon Kaen, Phuket, Rayong, Samut Songkhram, Phang Nga, and Mae Hong Son. In contrast, provinces in the lowest U5M decile (1.80 – 4.46 per 1,000 live births) were Kalasin, Pathum Thani, Yasothon, Lamphun, Nong Khai, Sukhothai, Nan, and Phayao.

In addition, Thailand faces a unique challenge: a declining fertility rate. Since 2019, the number of newborns per year has consistently been below 600,000 (Strategy and Planning Division, 2020). Moreover, in 2021, the number of newborns (544,570) fell short of the number of deaths (563,650) for the first time in Thailand's history (Department of Provincial Administration, 2020).This decline in fertility rate necessitates a deeper examination of U28MR and U5MR in Thailand. According to the World Health Organization (WHO), the mortality statistics reflect wider socio-economic issues that have direct implications on maternal and child health, the organization, and distribution of health services, socio-environmental conditions, and lifestyle behaviours (WHO, 2020). Furthermore, neonatal disorders and congenital birth defects contribute primarily to U28MR and U5M rates in Thailand (Strategy and Planning Division, 2020). The action plan by the Newborn Health WHO Team (2018) has reported that most neonatal deaths are preventable with simple, cost-effective interventions. Many of these deaths result from conditions and diseases like pre-term birth complications, intra-partum-related complications, and sepsis. Similarly, congenital birth defects could be prevented with improved maternal nutrition, control of maternal diseases, and prenatal screening.

Despite advances in understanding the causes of U28MR and U5MR, a clear spatial pattern and insight of the U5MR distribution across Thailand is lacking. This is a critical gap in our awareness as it inhibits the development of localized health policies and interventions. A spatially informed approach is necessary because health outcomes are significantly influenced by geographic variations, which correspond to disparities in socio-economic conditions, healthcare services, environmental conditions and lifestyle behaviours. Moreover, the declining birth rate in Thailand presents an evolving demographic landscape, posing newer challenges to the goal of reducing the U5MR. Against this backdrop, it is essential to re-evaluate the current understanding of U5MR in the country and determine how different variables interact in the spatial context impacting health outcomes in general.

In view of these gaps, this study aims to examine the spatial association and modelling of the U5MR in Thailand. It seeks to inform efforts to reduce U5MR amidst the scenario of a declining birth rate in the country. By bringing a spatial lens to U5MR, this study is poised to provide valuable data to health policymakers and stakeholders. It is expected that these data would then assist in planning and implementing effective preventive measures in a manner that is spatially informed and targeted, further enhancing the efficiency and effectiveness of such interventions.

Materials and Methods

This study is spatial, cross-sectional study designed to explore the relationship between various socioeconomic health-related variables and U5MR. We utilized geographic information systems (GIS) and spatial statistical tools to analyze U5MR across various provinces in Thailand with special reference to hotspots of high infant mortality.

Data collection

This study utilized multiple data sources, including health statistics from the Ministry of Public Health (Strategy and Planning Division, 2020), night-time lightdatafrom the visible infrared imaging radiometer suite (*VIIRS*) onboard the Suomi national polar-orbiting partnership (Suomi *NPP*) satellite (https://ncc.nesdis.noaa.gov/VIIRS/), data reports from the National Centers for Environmental Information (NCEI) of the U.S. National Oceanic and Atmospheric Administration (NOAA), and key statistical indicators from the Thai National Statistical Office of Thailand (2020) and Office of the National Economic and Social Development Council. The variables integrated into the models for analysis included low birth weight, children aged 0-5 years with age-appropriate development, average years of education, unemployment rate, community organizations, night-time luminosity, proportion of agricultural land use, number of physicians per 1,000 population, number of nurses per 1,000 population, number of hospital beds per 1,000 population, and exclusive breastfeeding.

Spatial analysis

We the GIS investigations, we used GeoDa™, version 1.18.0 to conduct spatial analysis and visualize U5MR across Thailand's provinces with aim of identifying patterns and potential clusters of high U5MR. A colour-coded system was used to create GIS maps showing variations in U5MR throughout the country.

Spatial autocorrelation

The first step in our analysis involved employing Global and Local Moran's *I* statistics to identify spatial autocorrelation in U5MR. The former was used to identify broad trends across the entire country, while the latter was used to pinpoint clusters or hotspots at the local level (Moran, 1948; Anselin, 1995).Global Moran's *I* was calculated using the equation:

$$I = \frac{\text{n}}{S_0} * \frac{Z_i Z_j W_{ij}}{Z_i^2} \qquad \text{(Eq.1)}$$

and the Local Moran's *I* computed by the equation:

$$I_1 = \frac{Z_i}{S_1} * Z_j W_{ij} \qquad \text{(Eq.2)}$$

where n is the total number of regions, S_0 the sum of all spatial weights, Z the deviation of the variable from its mean, $S_1$the sum of all the squared Zs, and W_{ij} the spatial weight between regions i and j. For this study, spatial autocorrelation was assessed using local indicators of spatial association (LISA), a category of statistics that includes various measures to detect different types of spatial patterns, including Moran's *I*. LISA was applied to assess global spatial autocorrelation in U5MR and associated factors.

Specifically, we utilized Moran's *I*, a measure within LISA, to identify whether individual regions were part of a spatial cluster of similar or dissimilar U5MR values (*i.e.* high-high or low-low clusters), and to identify outliers (*i.e.* high-low or low-high clusters).

This allowed us to visualize spatial disparities and pinpoint potential clusters or hotspots at the local level.

F-statistic was used in in the regression analysis to identify whether or not the means between two populations were significantly different.

Spatial econometric models

Once the presence of spatial autocorrelation was confirmed, regression models were developed to evaluate the association between various factors and U5MR. Ordinary Least Squares (OLS) was first used as a traditional method for comparing and verifying the spatial models. Its equation is:

$$Y = B_0 + B_1X + \varepsilon \quad \text{(Eq.3)}$$

where Y is the dependent variable, B_0 the y-intercept, B_1 the slope of the regression line (effect of X on Y), X the independent variable, and e is the error term (Wooldridge, 2013).

Subsequently, the spatial lag model (SLM) and the spatial error model (SEM) were employed to account for spatial autocorrelation. The SLM introduces a spatially lagged dependent variable into the equation as follows:

$$Y = \rho WY + X\beta + \varepsilon \quad \text{(Eq.4)}$$

where ρ is the spatial autoregressive parameter, and WY the spatially lagged dependent variable (spatial multiplier effect) (Anselin, 1988).The SEM incorporates spatial autocorrelation into the error term:

$$Y = X\beta + \lambda W_\varepsilon + \varepsilon \quad \text{(Eq.5)}$$

where λ is the spatial error coefficient, and $W\varepsilon$ the spatially autocorrelated error (LeSage & Pace, 2009). Following the confirmation of spatial autocorrelation, regression models were employed to explore the association between U5MR and various factors. Initially, the OLS model served as a conventional method for comparison and validation of spatial models. Further, the SLM and SEM were used to account for spatial autocorrelation. The selection of an optimal model among these would be based on a set of fit statistics, including the log-likelihood function, Akaike's Information Criterion (AIC), the Bayesian Information Criterion (BIC) and residual testing by Moran's *I*.

The the proportion of variance in the dependent variable that can be explained by the independent variable, *i.e.* goodness-of-fit (R^2), for each model was assessed using the log-likelihood, with higher values indicating a superior fit. Meanwhile, both AIC and BIC provide a balance between the goodness-of-fit and the complexity of each model. Lower values of AIC and BIC are generally preferred, as they indicate a model that has a good fit while also being parsimonious. Finally, to ensure that no spatial autocorrelation would remain unaccounted, the residuals in each model was by Moran's *I*.

By using this array of statistical and spatial analytical methods, it was possible to robustly examine the factors contributing to U5MR disparities in Thailand and thus ensure that the analysis was comprehensive, taking into account both the spatial nature of the data and the need for model parsimony.

Results

As depicted in Figure 1, GIS mapping revealed a distinct disparity in U5M across provinces. The spatial autocorrelation analysis revealed a significant positive correlation in the distribution of U5MR between neighbouring regions. The Moran's *I* value of 0.194 indicated that areas with high U5MRwere geographically clustered. High U5MR clusters (hotspots) were observed in the provinces of Krabi, Pattani, Yala, and Phatthalung. These high U5MR areas were statistically significant, showing a shared spatial distribution pattern as Figure 2.

The calculated Global Moran's *I* and the local indicators of spatial association (LISA) were utilized to identify the significance and spatial autocorrelation of various factors relating to U5MR (Figure 3).

Significant positive spatial autocorrelation was observed for low birth weight (I=0.201*) and unemployment rate (I=0.225*). On the other hand, average years of education (I=-0.113*) and

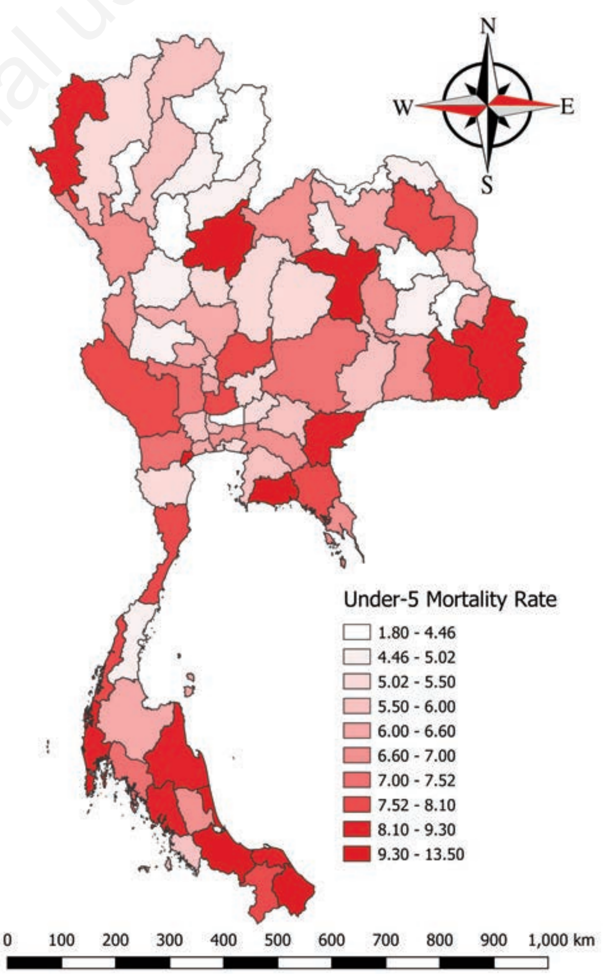

Figure 1. The under-5 mortality rate per 1,000 live births in Thailand in 2020.

community organizations (I=-0.118*) demonstrated significant negative spatial autocorrelation. In terms of local spatial clusters, regions like Krabi, Phatthalung, Pattani, and Yala showed high values of low birth weight, indicating higher U5MR, while regions such as Chiang Rai, Lampang, Phayao and Nan indicated low values, suggesting lower rates (Anselin, 1995).

The OLS, SLM and SEM results are shown in Table 1.

Both the OLS and the SLM revealed that low birth weight had a significant positive correlation with U5MR (OLS: 0.548; SLM: 0.56, p<0.05). The SEM confirmed these results and indicated an even stronger correlation (0.632, p<0.01).

While the influence of children aged 0-5 years with age-appropriate development was not statistically significant in all models, average years of education showed a significant negative correlation with U5MR (OLS: -0.889; SLM: -0.898; SEM: -0.872, p<0.01). This was indicative of its protective role against U5MR.

Community organizations also displayed a significant negative correlation with U5MR across all models (OLS: -0.396; SLM: -

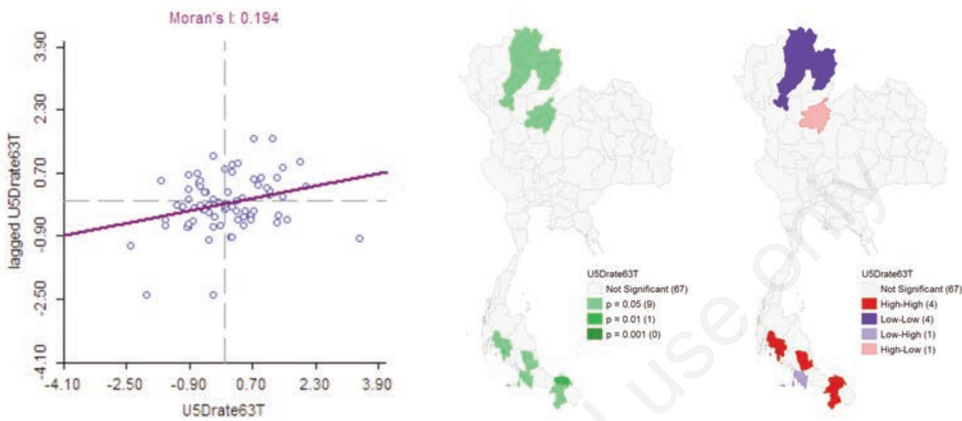

Figure 2. The distribution of Under-5 mortality rate based on Moran's I and the univariatelocal indicator of spatial autocorrelation (LISA); (a) Moran's *I*, (b) Spatial cluster, (c) Significant level of spatial cluster.

Table 1. Impact on under-5 mortality rates by variables investigated.

Variable	OLS coefficient (SE)	Spatial regression analysis SLM coefficient (SE)	SEM coefficient (SE)
Low birth weight (%)	0.548 (0.240)*	0.56 (0.22)*	0.632 (0.211)**
Children aged 0-5 years with age-appropriate development (%)	0.158 (0.195)	0.169 (0.179)	0.266 (0.17)
Average years of education	-0.889 (0.323)**	-0.898 (0.297)**	-0.872 (0.28)**
Unemployment rate (%)	0.235 (0.182)	0.243 (0.168)	0.233 (0.156)
Community organizations per 1,000 populations	-0.396 (0.144)**	-0.403 (0.134)**	-0.400 (0.130)**
Night-time luminosity (average pixel per year)	-0.172 (0.100)	-0.17 (0.092)	-0.187 (0.087)*
Proportion of agricultural land use (%)	1.736 (1.07)	1.763 (0.983)	1.782 (0.907)*
Physicians per 1,000 population	3.249 (1.938)	3.128 (1.805)	3.156 (1.732)
Nurses per 1,000 population	0.943 (0.633)	0.989 (0.594)	0.951 (0.528)
Hospital beds per 1,000 population	-1.484 (0.746)	-1.498 (0.686)*	-1.351 (0.635)*
Exclusive breastfeeding (%)	-0.043 (0.013)**	-0.043 (0.012)***	-0.043 (0.012)***
Constant	-2.006 (20.185)	-2.798 (18.509)	-13.798 (17.828)
ρ		-0.038 (0.111)	
λ (varies between 0.1 and 1.0)			-0.294 (0.137)*
F-statistic (minimum value = 0)	7.413		
R^2 (coefficient of determination)	0.560	0.561	0.588
Log likelihood	-129.984	-129.927	-128.533
AIC	283.969	285.854	281.066
BIC	311.938	316.154	309.035
Moran's *I*	-0.844		

*correlation significance at the 0.05 level; **correlation significance at the 0.01 level; ***correlation significance at the 0.001 level; OLS = ordinary least squares; SLM = spatial lag model; SEM = spatial error model; SE = standard error; Constant = the regression model intercept (the expected mean value of Y when all X=0); ρ = spatial autoregressive parameter; F-statistic = the ratio of two variances; λ = an indicator of the strength of the relationship between independent and dependent variables; AIC = Akaike's information criterion; BIC = Bayesian information criterion, R^2 = the goodness of fit.

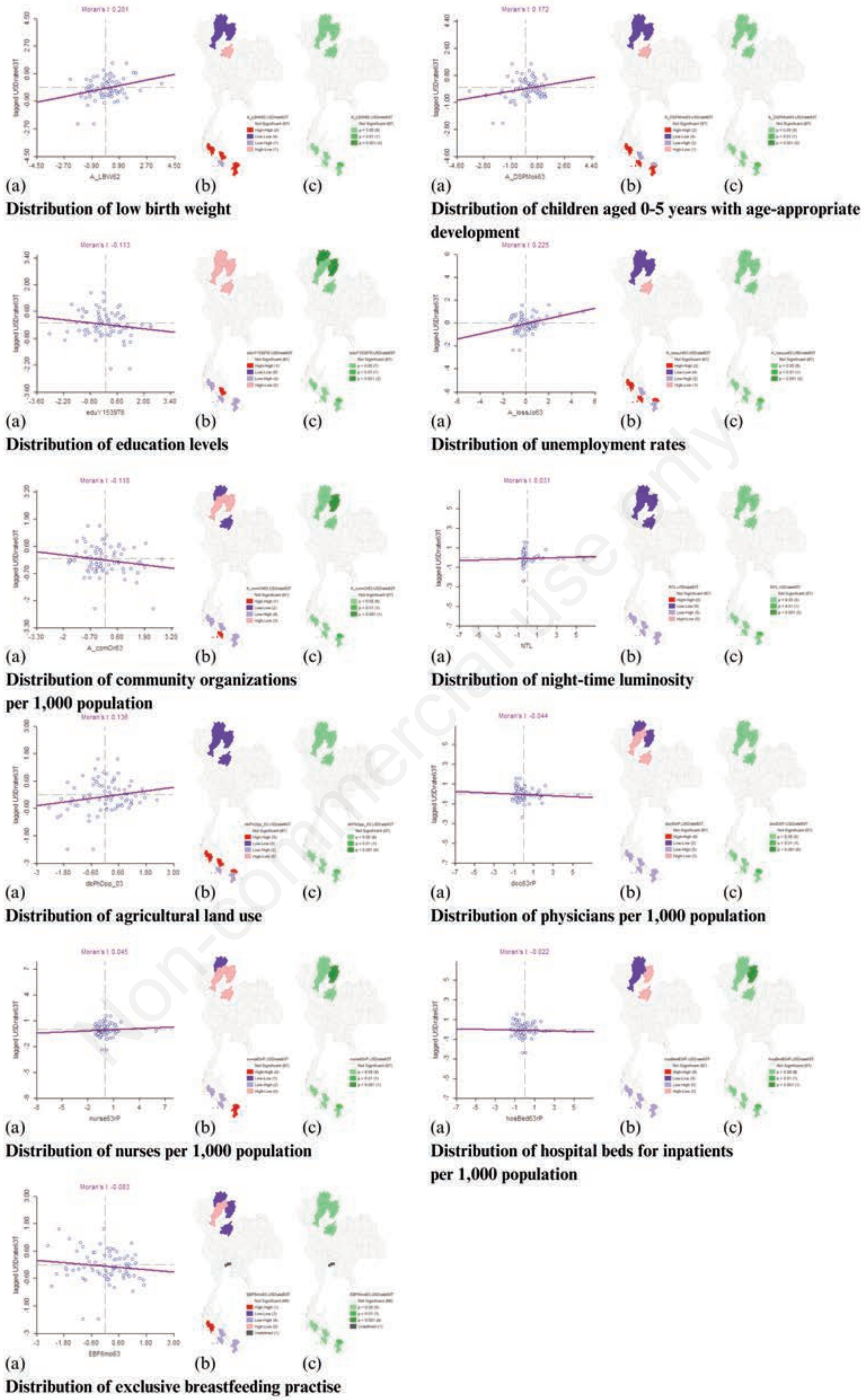

Figure 3. Moran's I and results of bivariate local indicator of spatial autocorrelation (LISA) of variables investigated and the Under-5 mortality rate; (a) Moran's *I*, (b) Spatial cluster, (c) Significant level of spatial cluster,

0.403; SEM: -0.400, p<0.01). Night-time luminosity was found to be significant in the SEM model (-0.187, p<0.05).

Additionally, the proportion of agricultural land use showed a significant positive correlation with U5MR in the SEM model (1.782, p<0.05), while the number of hospital beds per 1,000 population showed a significant negative correlation in the SLM and SEM models (SLM: -1.498; SEM: -1.351, p<0.05).

Finally, exclusive breastfeeding practices displayed a significant negative correlation with U5MR across all models (OLS: -0.043; SLM: -0.043; SEM: -0.043, p<0.001), indicating their protective influence.

In terms of model fitness, the OLS model generated an Akaike information criterion(AIC) of 283.969 and a Bayesian information criterion (BIC) of 311.938. Moran's *I* for the OLS residuals was -0.844, indicating a negative spatial autocorrelation and suggesting the presence of a spatial structure in the residuals, thus necessitating the application of spatial econometric models (Anselin & Bera, 1998).

The SLM, which included the spatially lagged dependent variable, reinforced the significance of the factors identified in the OLS and introduced number of hospital beds per 1,000 population as an additional significant factor. The SLM had an AIC of 285.854 and a BIC of 316.154. The Lagrange Multiplier (LM) lag test statistic was 0.037, implying that the SLM may not provide the best fitting model.

The SEM model had the highest R^2 value (0.588) with a λ value of -0.294 (p<0.05), suggesting it explained the most variance in U5MR. The SEM model also had the lowest AIC (281.066) and BIC (309.035), indicating it was the best fitting model. As seen in Figure 4, the lagged residual of Moran's *I* statistic was found to be -0.026, indicating that the SEM sufficiently handled the spatial dependence in the U5MR data. The LM error test statistic for the SEM was 1.514, supporting this inference. Overall, these results highlight both direct and indirect influences on U5MR, providing insights into the key factors that should be targeted for effective interventions.

Discussion

The path to reducing U5MR in Thailand is undoubtedly complex but not insurmountable. Our study has shed light on various determinants and their spatial correlation, offering valuable insights to inform future research and strategies. The challenge lies in translating these findings into effective, context-specific interventions that can drive meaningful progress in reducing U5MR, thereby ensuring a healthier future for Thailand's children.

Our study investigated the complex determinants of U5MR in Thailand which is key indicator of a nation's health, social and economic conditions. Drawing from diverse aspects of socio-economic development, healthcare access and child-specific health behaviours, our study outlined critical factors that could be instrumental in shaping future public health strategies and interventions. It seeks to provide insights into the complex determinants of U5MR within the Thai context, which identifies low birth weight and the unemployment rate as significant influencers of U5MR. Our findings align with those presented by the WHO (2022) and the research by Dooley and Prause (Dooley & Prause, 2005). Low birth weight, typically resulting from pre-term birth or inadequate prenatal care, can lead to various immediate health issues, including a heightened risk of mortality (WHO, 2022). These findings emphasize the need for interventions to improve prenatal and maternity care in efforts to decrease U5MR.

Interpretation of findings

The association between U5MR and unemployment rate indicates the crucial role the broader socio-economic conditions play in determining child health outcomes. Reduced household income, due to unemployment, can limit access to necessary healthcare services and nutritional needs, both of which are essential for child health and survival (Dooley & Prause, 2005). Thus, policies aimed at socio-economic development may indirectly contribute to a reduction in U5MR.Our results resonate with findings from Ghana (Aheto et al., 2020), Gambia (Quattrochi et al., 2015), Nigeria (Alabi et al., 2016; Noori et al., 2021), and Ethiopia (Liyew et al., 2021), where correlations between U5MR and various socio-economic and environmental factors like ethnicity, household income, healthcare access, sanitation and living conditions have been observed. These studies, like ours, emphasize the multifaceted nature of child mortality, extending beyond pure health factors to encompass a broader set of social determinants.

The proportion of agricultural land use also revealed a signifi-

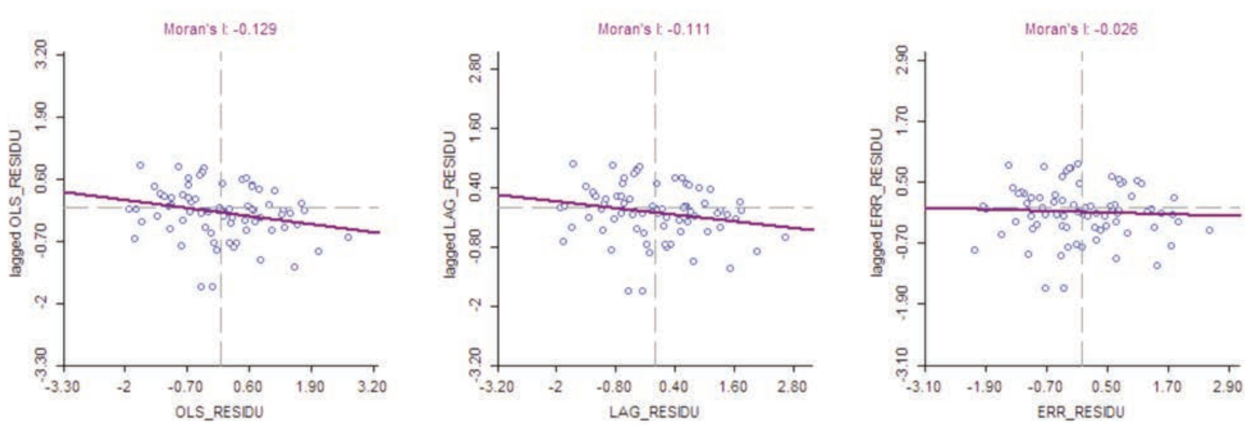

Figure 4. Moran's *I* scatter plot for the relative OLS, SLM and SEM residuals.

cant correlation with U5MR. This supports findings that suggest the impact of agricultural practices on child health outcomes, often due to factors such as the use of pesticides, water quality and food security (Fenske *et al.*, 2000; Ward *et al.*, 2018). It underscores the importance of promoting safer farming practices and improving rural healthcare services. Moreover, the impact of land usage for agricultural purposes on U5MR also indicates the importance of safe agricultural practices and interventions focusing on rural healthcare access.

The number of hospital beds per 1,000 population, an indicator of healthcare access, exhibited a significant inverse relation to U5MR. Adequate bed capacity is essential for providing effective acute and routine care, thereby reducing under-5 deaths (Aregbeshola & Khan, 2018; Wagstaff & Claeson, 2004). Therefore, our findings point towards strengthening the health infrastructure as an effective strategy to combat U5MR in Thailand.

Spatial correlation in U5MR determinants, suggesting regional clustering of mortality rates, was another significant outcome of our study, mirroring findings in Ethiopia (Liyew *et al.*, 2021) and Egypt (Hassan *et al.*, 2021). These results counter those from a study covering 35 African countries that found no clear geographical patterns in child mortality (Li *et al.*, 2019). Instead, our findings suggest significant spatial factors shaping U5MR in Thailand.

The protective effect on child survival of exclusive breastfeeding practices, highlighted in our study, aligns with findings from Lesotho (Zondi *et al.*, 2020). The first six months of exclusive breastfeeding provide significant health benefits and immunity against common childhood illnesses, contributing substantially to reducing child mortality (Victora *et al.*, 2016; WHO, 2001).

Other protective factors revealed include average years of education and the presence of community organizations. Education, especially among women, promotes improved health-seeking behaviours, informed nutrition choices, and increased utilization of preventive care, collectively contributing to reduced child mortality (Gakidou *et al.*, 2010; Kuhn, 2010). Community organizations, acting as robust social support networks, were also associated with lower U5MR. Such organizations can bolster child health through educational activities, resource provision, and improved access to services (Pronyk *et al.*, 2008). These findings underscore the necessity for comprehensive strategies that span beyond the health sector to effectively combat child mortality.In addition, our study also reveals a high U28MR, a finding that echoes a study from Egypt (Hassan *et al.*, 2021), highlighting the importance of interventions aimed at neonatal care and addressing low birth weight, a common risk factor for neonatal deaths.

Limitations

Despite offering novel insights, our study acknowledges limitations common in spatial epidemiological research, including data availability (Jutte *et al.*, 2011), the cross-sectional study design (Szklo & Nieto, 2007), potential ecological fallacy (Piantadosi *et al.*, 1988), unmeasured confounding factors (Marmot, 2005), and limitations related to spatial autocorrelation (Anselin, 1988).

The revealed regional disparities in U5MR highlight the importance of context-specific interventions tailored to the unique needs and conditions of each region. A uniform approach may not yield optimal results; instead, targeted strategies based on regional characteristics, and the spatial distribution of influential factors should be developed and implemented.

We must underscore that U5MR is an issue of national importance, mirroring broader social, economic, and health conditions. Therefore, efforts to reduce U5MR should be considered part of larger initiatives to improve overall societal well-being and development. Achieving Thailand's child health objectives necessitates a concerted, multi-faceted approach that spans across multiple sectors and encompasses diverse strategies.

Conclusions

Our study has elucidated several key determinants of U5MR in Thailand, revealing a complex web of socio-economic, healthcare, and behavioural factors. Most notably, low birth weight and unemployment rate emerged as significant predictors that exert a direct influence on U5MR. Meanwhile, protective factors such as average years of education, community organizations, the number of beds for inpatients per 1,000 population, and exclusive breastfeeding practices associated with lower U5MR, underscore the value of these components in improving child survival rates.

These findings significantly deepen our understanding of U5MR, pointing towards crucial policy implications. Indeed, strategies to reduce U5MR must transcend healthcare interventions to address root socio-economic determinants. We emphasize the need for comprehensive, multi-sectoral strategies that encompass socio-economic development to combat unemployment, health education to improve maternal and childcare practices, bolstering healthcare infrastructure, notably the number of inpatient beds per 1,000 population and harnessing the power of community organizations.

Recommendations

Suggestions for future research

Building on the significant associations observed in our study, future research should indeed investigate the diverse factors contributing to U5MR in Thailand further. Expanding on our findings, subsequent investigations could study the role of health infrastructure, especially the number of inpatient beds per 1,000 population, in shaping child health outcomes. Detailed data analyses could factor in localized community characteristics, individual behaviours, and family dynamics, offering more insights into their influence on child health outcomes as explained by Bhutta *et al.* (2014).

Further, understanding regional disparities in U5MR is crucial. Longitudinal studies would be invaluable in establishing the temporal relationship between identified factors and U5MR, providing stronger evidence for intervention design. Incorporating advanced statistical modelling techniques could better account for the complexity and multifaceted nature of these disparities as described by the United Nations Children's Fund *et al.* (2021).

Moreover, considering our findings on the proportion of land used for agricultural purposes, future research should explore how agricultural practices and related environmental factors might impact child health outcomes, with a focus on rural areas where agriculture is a significant occupation.

Policy recommendations

Our findings recommend the implementation of multi-sectoral strategies to address U5MR in Thailand. This includes improving socio-economic conditions, enhancing the quality and accessibility of healthcare, expanding health infrastructure, particularly the number of inpatient beds per 1,000 population, and addressing environmental health issues in regions with high U5MR.

Efforts should be directed towards addressing the impacts of low birth weight and unemployment rates, which were identified as significant contributors to U5MR. Initiatives might involve enhancing maternal health and nutrition during pregnancy to reduce instances of low birth weight and devising strategies to increase employment opportunities and economic stability in areas with high U5MR (see Bhutta *et al.*, 2014). Further, enhancing the protective factors identified in our study, such as average years of education, presence of community organizations, and exclusive breastfeeding practices, could lead to substantial improvements in U5MR. Potential strategies might involve investing in education, fostering community organizations, improving healthcare infrastructure, expanding inpatient bed capacity, and promoting exclusive breastfeeding practices through community health education as outlined by Mulholland *et al.* (2008) and followed up through the Newborn Health WHO Team (2018).

In addition, considering the spatial disparity identified in our study, targeted interventions should be considered for regions with high U5MR, including those with high proportions of land used for agricultural purposes. Safer farming practices and improving access to healthcare in rural areas should be integral components of such interventions.

Finally, adopting an equity-focused approach is essential. Reducing inequities in child health can lead to significant overall improvements in child health and survival rates. Thus, interventions should be designed and implemented to reach the most vulnerable and disadvantaged children and families, ensuring their inclusion and prioritization as shown by Victora *et al.* (2008) and Amouzou *et al.* (2012).

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