Spatial autocorrelation pattern of COVID-19 vaccine coverage in Thailand 2021 and 2022

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Abstract

During the COVID-19 pandemic in 2021–2022, vaccination against this infection was crucial for Thailand's recovery. This research aimed to identify spatial patterns of association between the distribution and spread of the COVID-19 pandemic on the one hand and vaccine coverage, health service and socio-economic factors on the other. Univariate analysis using Getis-Ord GI* found strong clustering of the vaccine coverage, mostly in Eastern, Central, and Southern regions (Andaman coast), while bivariate analysis using Moran's *I* revealed significant positive spatial correlation vaccine coverage with the presence of COVID-19 patients (2021 = 0.273; 2022 = 0.273), Night Time Light (NTL) (2021 = 0.159; 2022 = 0.118) and medical personnel (2021 = 0.174; 2022 = 0.123). In addition, Local Indicators of Spatial Association (LISA) analysis found High-High clusters predominantly in the Eastern and Central regions. Areas with high economic growth (as reflected by high NTL) had greater COVID-19 vaccine coverage, likely due to better access to information and efficient transport systems in areas with stronger financial resources than elsewhere. These factors facilitated access to healthcare ensured presence of adequate personnel and enabled rapid distribution of the vaccine. Additionally, high rates of COVID-19 infections increased public awareness of infection risk leading to better vaccination uptake. Policymakers should prioritise vaccine distribution in high-risk and underserved areas to ensure equitable access. Additionally, increasing health workforce capacity is essential to improving service efficiency and readiness for future outbreaks.

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Key words: COVID-19 vaccine coverage; GIS; Gtis-Ord GI*; Moran's I; LISA; Thailand.

Conflict of interest: the authors declare no potential conflict of interest, and all authors confirm accuracy.

Availability of data and materials: all data generated or analyzed during this study are included in this published article.

Ethics approval: ethical clearance for this study was obtained from the Khon Kaen University Ethics Committee, in Khon Kaen, Thailand (reference no. 660201.2.3/1520 Project ID HE672054).

Received: 17 December 2024.
Accepted: 26 March 2024.

Geospatial Health 2025; 20:1368
doi:10.4081/gh.2025.1368

Introduction

In late 2019, a coronavirus disease (COVID-19), not previously detected in humans was discovered in a hospital in China. This disease, called is a primarily respiratory illnesses that spreads through coughing, sneezing, or contact with infected secretions (Department of Disease Control, 2021). Thre years later, World Health Organization (WHO) reported 700 million COVID-19 cases worldwide, with 7 million fatalities (WHO, 2023), whilein Thailand, 4.7 million were confirmed infected and a total of 33,669 people died (Department of Disease Control, 2023). Beyond health impact, the COVID-19 pandemic had repercussions both health-wise for society and for the economy in general. In order to find a way to move Thailand out of the COVID-19 crisis and rapidly get Thailand back to normal, the government collaborated with all sectors. As soon as COVID-19 vaccines became available by the end of 2020, the Ministry of Public Health (MoPH) required the vaccine against this disease to be given with good coverage as quickly as possible as it would lower the risk of infection, prevent serious illness, lower death rates and fostering community immunity (Huang *et al.*, 2022). MoPH (2023) reported that 85 million doses were administered in 2021 covering 37.6 million individuals (with at least two doses). The cumulative total reached 116.7 million doses and 44.6 million fully vaccinated by the end of 2022 (MoPH, 2023). Socioeconomic factors, such as highly urbanised centres with education, industry and business establishments together with public transit systems have an indirect influence making it easier for people to access the healthcare system and be vaccinated (Department of Health, 2021; Williams *et al.*, 2022; Petrovici *et al.*, 2023; Chen *et al.*, 2023). Medical personnel were the first to receive the vaccine to assure that they would be able to carry out their work. The widespread morbidity and death rates of COVID-19 created public awareness and interest to receive the vaccine (Praboromarajchanok Institute, 2021; Pallathadka *et al.*, 2022; Fan *et al.*, 2022; MoPH, 2023).

Analytical methods in the form of spatial statistics and geographic information systems (GIS) provide clear visualisation making data easier to interpret (Utzinger *et al.*, 2011). The objectives of this research were to identify the spatial pattern of the COVID-19 pandemic in the 2021-2022 period, its association with vaccine coverage and role of socioeconomic and health service factors. Our aim was to provide spatial vaccine coverage information to be applied for the vaccinations planned for the following year. It would include policy-making, formulating guidelines for developing the health service system, overall problem-solving at the provincial level as well as supporting manpower and resources for the work on immunisation and prevention of COVID-19 in each area.

Materials and Methods

Spatiotemporal basis of the study

This study was conducted from 2021 to 2022 in Thailand, which covers 514,000 km² in Southeast Asia bordering Myanmar, Cambodia, Laos and Malaysia. The country is administratively divided into 76 provinces and 1 special administrative region, Bangkok. This research collected data from reports by the public health offices of all 76 provinces except Bangkok, which is therefore classified as null in the figures. Thailand is further grouped into six regions: Northern, Central, North-eastern, Eastern, Western and Southern, which provide a structured framework for analyzing spatial variations in COVID-19 vaccine coverage, highlighting regional disparities and clustering patterns influenced by socio-economic conditions, healthcare infrastructure and epidemic severity. The integration of geographic coordinates with administrative boundaries enables precise spatial statistical analysis, enhancing the detection of spatial autocorrelation. To support this analysis, we utilized DIVA-GIS (http://www.diva-gis.org/), an open-source tool for spatial data visualization and processing. This application played a key role in defining the study area, aligning administrative boundaries with georeferenced epidemiological and socio-economic data, ensuring accurate spatial representation and robust statistical analysis.

Design and data collection

This cross-sectional research is based on secondary data from multiple resources. For health service, COVID-19patients per 1,000 population, medical personnel per 1,000 population and vaccine distribution were gathered from MoPH (2022) and the Department of Disease Control (2022). For access to healthcare and vaccination, we used annual Night Time Light (NTL) average as it reflects the distribution of Thailand's on socioeconomic activities, such as urbanisation, industrial activities, population density and household income (Sangkasem & Puttanapong, 2022). The NTL data, expressed in digital numbers (DNs), were obtained from the Earth Observation Group - EOG (2022). High NTL values not only indicate.

Statistical analysis

We used QGIS to manage the spatial data (Steiniger & Hunter, 2013) and present the results in map format. The data were classified into deciles rank (10 groups) with respect to vaccination coverage. GeoDa (Anselin *et al.*, 2006) was used for univariate spatial autocorrelation analysis by global Moran's I (1950), with Getis-Ord GI* (1992) for hotspot analysis. The method Local Indicators of Spatial Association (LISA) (Ord, 1995) was used for bivariate analysis of epidemic, socio-economic and health service factors associated with vaccination coverage (two doses). The boundaries of areas with common borders were determined according to the principle of a spatial weight matrix using a Distance Band (DB) of 111.25 km, which was selected based on the average nearest neighbour distance between provincial centroids in Thailand. This threshold ensured that each province had a sufficient number of neighbouring units for robust spatial analysis while maintaining meaningful regional differentiation. The choice of this distance enhanced the reliability of spatial autocorrelation measures by balancing local and global spatial dependencies.

This study examined spatial relationships by analyzing each variable separately rather than using a multivariate approach. This approach allows for a clearer interpretation of how each factor – such as socio-economic status, healthcare access or epidemic severity – independently influences the vaccination coverage. By isolating these variables, the analysis highlights distinct spatial patterns and provides targeted insights for public health interventions, thereby enhancing the understanding of specific drivers of vaccine distribution and eventually leading to more precise policy decisions.

Getis-Ord GI* spatial correlation is a local spatial autocorrelation technique (Getis, and Ord, 1992), where G values close to or equal to 0 indicate randomness, while positive G values indicate a clustered pattern of the variable under investigation (hotspots) and negative G values the opposite, *i.e.* low levels of the variable in question (coldspots). We used this statistic in a univariate way for the study of the vaccination coverage applying the equation (Eq.):

$$Gi^* = \frac{\sum_{j=1}^{n} w_{ij} x_j - \bar{x}}{\sqrt{\left(\sum_{j=1}^{n} w_{ij}\right) s^2}} \qquad \text{Eq. 1}$$

where GI^* is the standardised mean of G at any position; X_j the vaccination coverage at position j; $\bar{x}$ the mean of the vaccination coverage; w_{ij} the weighted values at positions i and j; n the total vaccination coverage; and s the Standard Deviation (SD)

Moran's I statistic (1950) is a global spatial autocorrelation that can be presented as a scatter plot where values around 0 indicate randomness and values close to +1or -1 show spatial autocorrelation, the former positive with high, similar values close together and the latter the opposite, *i.e.* negative meaning that low such values are close together.It is calculated by the following formula:

$$I = \frac{N \sum_i \sum_j w_{ij} (X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2 \sum_i \sum_j w_{ij}} \qquad \text{Eq. 2}$$

where I is Moran's index; X the variable of interest; X_i the variable at location i; X_j the variable at location j; $\bar{x}$ the mean of X; N the number of spatial units at i and j; W_{ij} the weight applied to $i$and j, X_i - $\bar{x}$ the deviation of X_i from its mean; X_j - $\bar{x}$ the deviation of X_j from its mean. The significance level was set at p<0.05 with 999 permutations, a standard practice for assessing the reliability of spatial autocorrelation.

Local correlation was studied by producing LISA cluster maps (Anselin, 1995), where a clustered pattern of the variables under investigation next to each other are given as High-High (HH)and low levels of the variables in question near each other as Low-Low (LL), while mixed patterns either of High-Low (HL) or Low-High (LH) are outliers

$$I = \frac{(X_i - \bar{x})\Sigma_j w_{ij}(X_j - \bar{x})}{s_i^2}$$

$$s_i^2 = \frac{\Sigma_j (X_j - \bar{x})^2}{(N - 1)} \quad \text{Eq. 3}$$

where I is the Local Moran's index, with other symbols the same as those given for Eq. 1 and Eq. 2 above.

Results

In 2021, the average vaccination coverage against COVID-19 (2 doses) in Thailand was 58.5%, with Chonburi having the highest (87.7%) and Nong Bua Lamphu the lowest (39.5%). The highest group of the decile rank had a vaccination coverage range between 72.9% and 87.7% and included the following provinces: Chonburi, Phuket, Samut Sakhon, Chiang Mai, Pathum Thani, Rayong, Chachoengsao and Phang Nga (Figure 1).

In 2022, the average coverage was 73.0%, with Phuket Province showing the highest coverage (91.6%), while Narathiwat had the lowest (46.2%). According to decile rank, the highest percentage group of vaccinations (82.8–91.6%) included Phuket, Rayong, Pathum Thani, Ranong, Samut Prakan, Chonburi, Lamphun and Nakhon Pathom (Figure 1).

Univariate analysis

In 2021, hotspots ofvaccination coverage were found in 12 provinces: Chonburi, Rayong, Chanthaburi, Chachoengsao, Prachinburi, Nakhon Nayok, Nakhon Pathom, Samut Prakan, Samut Songkhram, Krabi, Phang Nga and Surat Thani. The opposite, areas where vaccination had not been carried out (coldspots) were found in 11 other provinces: Bueng Kan, Amnat Charoen, Khon Kaen, Udon Thani, Loei, Nong Khai, Roi Et, Kalasin, Sakon Nakhon, Mukdahan and Yala (Figure 2).

In 2022, hotspots were found in 11 provinces: Chonburi, Rayong, Chanthaburi, Chachoengsao, Nakhon Nayok, Samut Prakan, Samut Sakhon, Samut Songkhram, Krabi, Phang Nga, and Lampang, with coldspots in 4 provinces: Songkhla, Pattani, Yala and Narathiwat (Figure 2). Compared to 2021, the number of coldspotsdecreased due to the more widely distribution of vaccines in 2022.

Bivariate analysis

Vaccine coverage and COVID-19 patients per 1,000 population

Moran's I indicated a positive spatial correlation between the distribution pattern of COVID-19 patients and vaccine coverage in both 2021 (0.273) and 2022 (0.273). LISA gave a similar picture with high COVID-19 vaccine coverage and high numbers of COVID-19 patients per 1,000 population in many areas. In 2021, there were 9 HH provinces: Chonburi, Rayong, Samut Prakan, Samut Songkhram, Prachinburi, Chachoengsao, Nakhon Nayok, Chanthaburi and Nakhon Pathom, while 10 provinces exhibited LL results: Udon Thani, Khon Kaen, Roi Et, Kalasin, Nong Khai, Amnat Charoen, Mukdahan, Loei, Sakon Nakhon and Bueng Kan. In 2022, there were again 9 HH provinces, many of them the same as in 2021s: Chonburi, Rayong, Samut Sakhon, Samut Prakan, Samut Songkhram, Chachoengsao, Nakhon Nayok, Chanthaburi and Phang Nga, but only 4 LL provinces: Yala, Pattani, Narathiwat and Songkhla (Table 1 and Figure 3).

Vaccine coverage and socioeconomic factors (as defined by NTL)

Moran'sI indicated a positive spatial correlation between the distribution pattern NLT and that of COVID-19 vaccine coverage in both 2021 (0.159) and 2022 (0.118). LISA identified 6 HH provinces with high COVID-19 vaccine coverage and high NTL values in 2021: Chonburi, Samut Prakan, Rayong, Chachoengsao, Nakhon Pathom, and Samut Songkhram, with 11 LL provinces: Bueng Kan, Amnat Charoen, Khon Kaen, Udon Thani, Loei, Nong

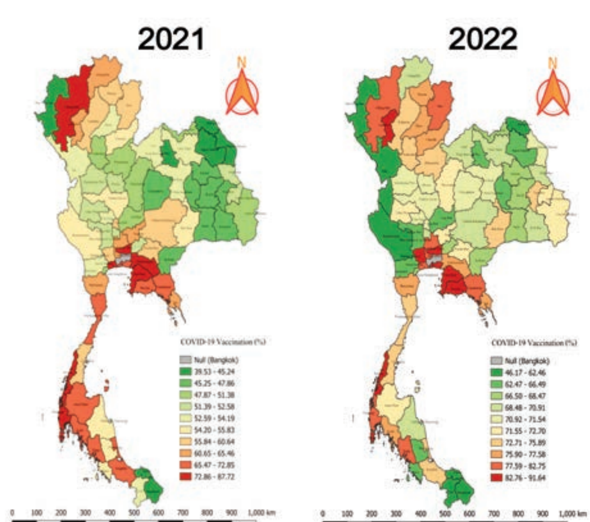

Figure 1. Annual data on vaccine coverage for the first two years of the COVID-19 pandemic in Thailand.

Khai, Roi Et, Kalasin, Sakon Nakhon, Mukdahan, and Yala.This picture had improved in 2022, as there were only 3 LL provinces: Yala, Narathiwat, and Songkhla and the HH provinces remained at 6, many of them the same as in 2021: Chonburi, Samut Prakan, Rayong, Chachoengsao, Samut Sakhon and Samut Songkhram (Table 2 and Figure 4).

Vaccine coverage and and medical personnel per 1,000 population

Moran'sI indicated spatial positive correlation between the distribution pattern of medical personnel (expressed per 1,000 population) with vaccine coverage in both 2021 (0.174) and 2022 (0.123). LISA indicated 8 HH provinces with high COVID-19 vaccine coverage and high numbers of medical personnel in 2021: Chonburi, Rayong, Chanthaburi, Nakhon Nayok, Nakhon Pathom, Samut Songkhram, Phang Nga and Surat Thani, with 9 LL provinces: Amnat Charoen, Bueng Kan, Udon Thani, Loei, Nong Khai, Roi Et, Kalasin, Sakon Nakhon, and Mukdahan. With 8 HH provinces in 2022, many of them the same as in 2021: Chonburi, Rayong, Chanthaburi, Nakhon Nayok, Lampang, Samut Sakhon, Samut Songkhram, and Phang Nga but only 2 LL provinces: Pattani and Narathiwatthe, situation had improved also for this measure (Table 3 and Figure 5).

Table 1. Spatial correlation between the COVID-19 pandemic and vaccine coverage.

Year	LISA High-High	High-Low	Low-Low	Low-High
2021 Moran's I = 0.273 p=0.001	Chonburi* Rayong** Samut Prakan** Samut Songkhram** Chachoengsao** Nakhon Nayok* Chanthaburi** Nakhon Pathom* Prachinburi*	Yala**	Udon Thani** Khon Kaen** Roi Et* Kalasin* Nong Khai** Amnat Charoen* Mukdahan** Loei** Sakon Nakhon** Bueng Kan*	Phang Nga* Krabi** Surat Thani* Mae Hong Son*
2022 Moran's I = 0.273 p=0.001	Chonburi** Rayong* Samut Sakhon* Samut Prakan** Samut Songkhram** Chachoengsao** Nakhon Nayok* Chanthaburi* Phang Nga*	None	Yala** Pattani** Narathiwat*** Songkhla*	Chumphon* Krabi* Lampang*

*significant at the 0.05 level; **significant at the 0.01 level; ***significant at the 0.001 level.

Table 2. Spatial correlation between nighttime light and vaccine coverage.

Year	LISA High-High	High-Low	Low-Low	Low-High
2021 Moran's I = 0.159 p = 0.004	Chonburi* Samut Prakan** Rayong** Chachoengsao** Nakhon Pathom* Samut Songkhram**	None	Bueng Kan* Amnat Charoen* Khon Kaen** Udon Thani** Loei** Nong Khai** Roi Et* Kalasin* Sakon Nakhon** Mukdahan** Yala**	Chanthaburi** Prachinburi* Nakhon Nayok* Mae Hong Son* Krabi** Phang Nga* Surat Thani*
2022 Moran's I = 0.118 p=0.008	Chonburi** Samut Prakan** Rayong* Chachoengsao** Samut Sakhon* Samut Songkhram**	Pattani**	Songkhla* Yala** Narathiwat***	Nakhon Nayok* Chanthaburi* Lampang* Krabi* Phang Nga* Chumphon*

*significant at the 0.05 level; **significant at the 0.01 level; ***significant at the 0.001 level.

Discussion

Unlike conventional vaccine coverage studies that rely on aggregate national or regional statistics, this study employed spatial autocorrelation techniques to uncover local disparities in vaccine accessibility. By integrating spatial analysis with socio-economic and healthcare service factors, we were able to provide a nuanced understanding of how these variables interact spatially, offering actionable insights for targeted public health interventions. The use of both global and local correlation statistics allowed for a more rigorous assessment of vaccine coverage in relation to needs due to increased risk. These techniques go beyond traditional correlation analysis by considering geographic relationships, which reduces the risk of misinterpreting random associations as meaningful patterns. This approach should enable policy makers to identify critical gaps and optimize resource allocation for future vaccination campaigns. Our LISA results of high numbers of COVID-19 patients and high vaccine coverage in central

Table 3. Spatial autocorrelation between medical personnel and COVID-19 vaccine coverage.

Year	LISA High-High	High-Low	Low-Low	Low-High
2021 Moran's *I*= 0.174 p=0.001	Chonburi* Rayong** Chanthaburi** Nakhon Nayok* Nakhon Pathom* Samut Songkhram** Phang Nga* Surat Thani*	Khon Kaen** Yala**	Amnat Charoen* Bueng Kan* Udon Thani** Loei** Nong Khai** Roi Et* Kalasin* Sakon Nakhon** Mukdahan**	Chachoengsao** Samut Prakan** Prachin Buri* Mae Hong Son* Krabi**
2022 Moran's *I* = 0.123 p=0.005	Chonburi** Rayong* Chanthaburi* Nakhon Nayok* Chumphon* Lampang* Samut Sakhon* Samut Songkhram** Phang Nga*	Songkhla* Yala**	Pattani** Narathiwat***	Samut Prakan** Chachoengsao** Krabi*

*significant at the 0.05 level; **significant at the 0.01 level; ***significant at the 0.001 level.

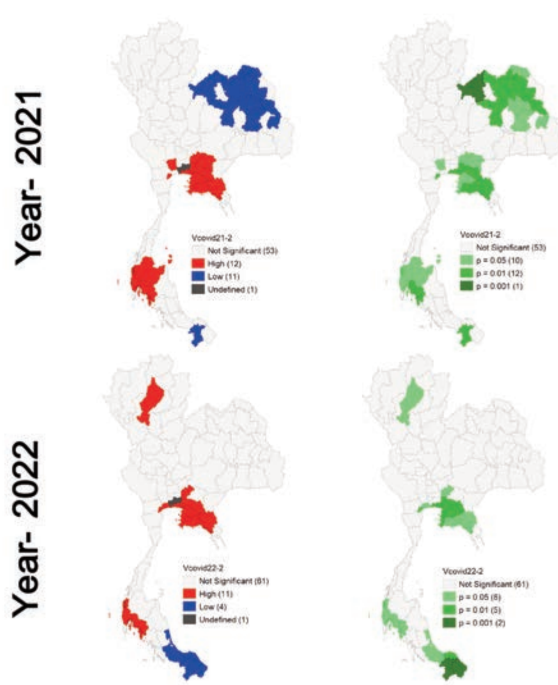

Figure 2. Local autocorrelation ofvaccine coverage in Thailand. High vaccine coverage in red, low vaccine coverage in green.

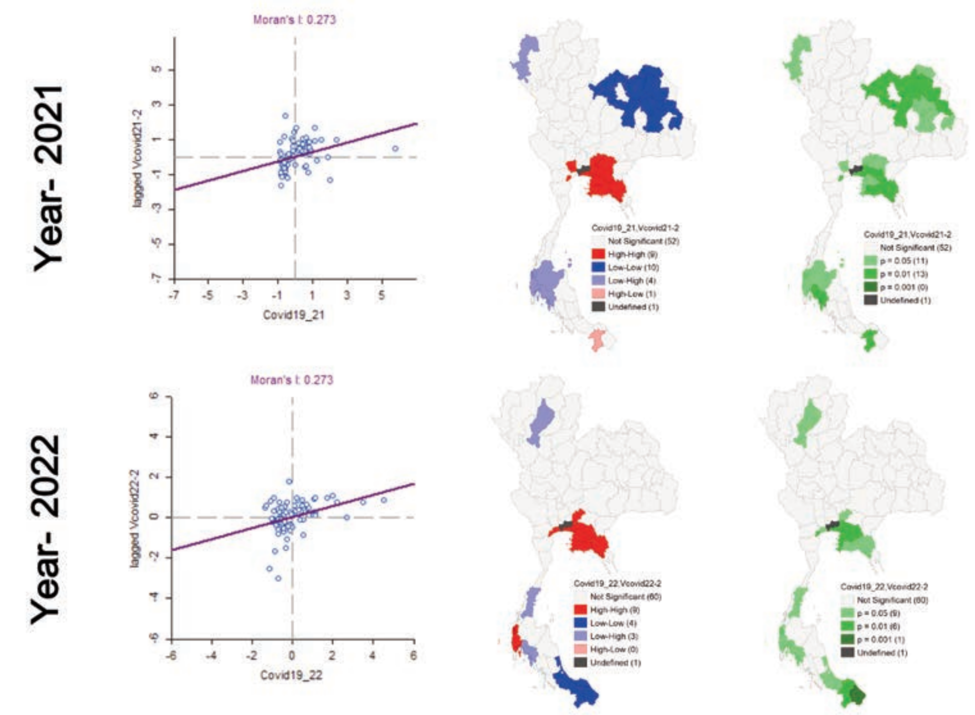

Figure 3. Levels of correlation between COVID-19 pandemic and vaccinecoverage in Thailand

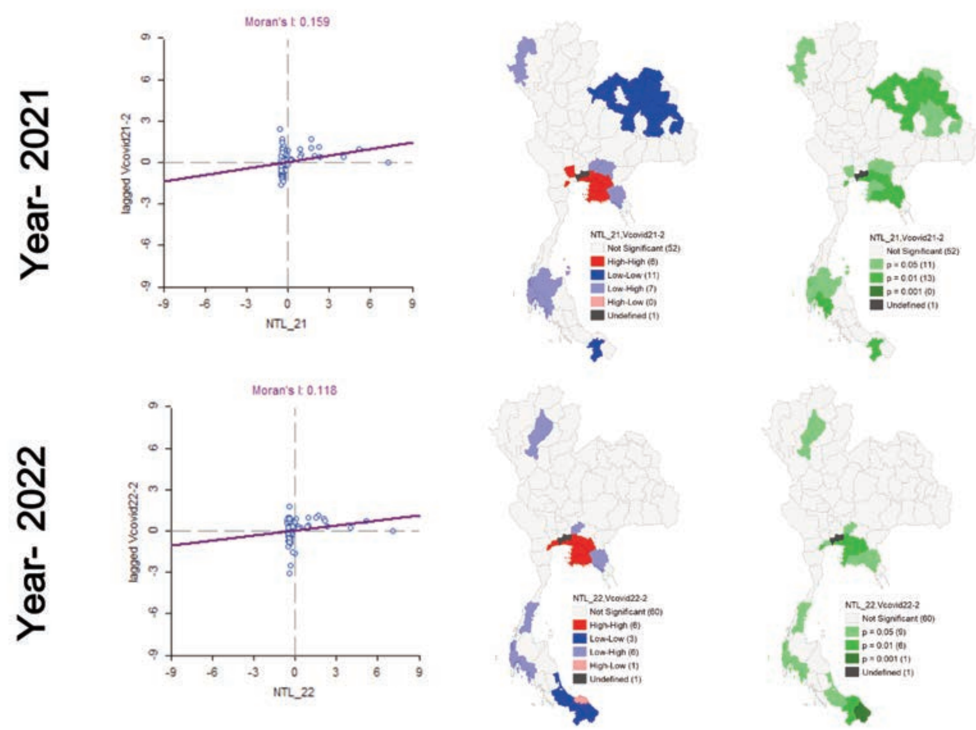

Figure 4. Levels of correlationbetween nighttime light and vaccine coverage in Thailand.

and eastern regions of Thailand should be interpreted as the initial outbreaks there actually encouraged people to be vaccinated thereby containing the perspective of even larger outbreaks. This has been reported from Europe, where countries with low vaccine coverage due to hesitancy about effectiveness, safety and side effects of the vaccines offered had a larger problem (Fan *et al.*, 2022). Consistent with the study of a systematic review and meta-analysis (Galanis *et al.*, 2021), our results found that perception of risk, taking care of risk groups and confidence in the COVID-19 vaccines were associated with containment of the infection. This increased public confidence in the COVID-19 vaccine, while unwillingness of health care workers to receive vaccination had the opposite effect (Huang & Cutter, 2022).

Since areas characterized by NTL tend to be metropolitan with restaurants, shops, hotels, and tourism with access to information and technology, these areas are likely to also have the resources to implement and support effective vaccination programmes. This is especially the case in Chonburi and Phuket provinces, where we also found high vaccine coverage in line with the COVID-19 guidelines demanding that businesses comply with vaccinations. These guidelines include also the educational sector, where large number of students as well as school children had to be vaccinated before the start of the school year (Department of Health, 2021).The health service centreshave good management systems are an important part of the vaccination structure and can support a large number of people as they aregenerally located in areas where people can easily access them (Ministry of Public Health, 2018). This is consistent with studies in the United States (Diesel *et al*., 2021) and Romania (Petrovici *et al.*, 2023) that similarly stated that the majority of people who received the COVID-19 vaccine were people living in urban areas, especially in large cities. Therefore, social factors, including average income, education and employment are associated with COVID-19 vaccine coverage (Williams *et al.*, 2022).

Importantly, we found areas with sufficient medical staff to be associated with good COVID-19 vaccine coverage in both 2021 and 2022. The explanation must be that areas with a large number of medical personnel have the capacity to provide vaccines rapidly as the workforce can be dividedinto several units that provide the vaccines to people in areas easily accessible to the public so people do not have to wait long. In addition, the fact that the medical had all been vaccinatedcreated confidence and reduces concerns among the public. When comparing the two years' findings, it was discovered that in 2021, the majority of the Northeast area had poor COVID-19 immunization rates and limited number of medical workers. Later in 2022, the underserved areas there had disappeared because, even though there were few personnel, operations continued until the Northeast region had reached vaccination coverage no different from other areas. This result indicates that personnel are of key importance for the vaccination operations.

This was a cross-sectional geographic information study, capturing relationships only within the studied period. While correla-

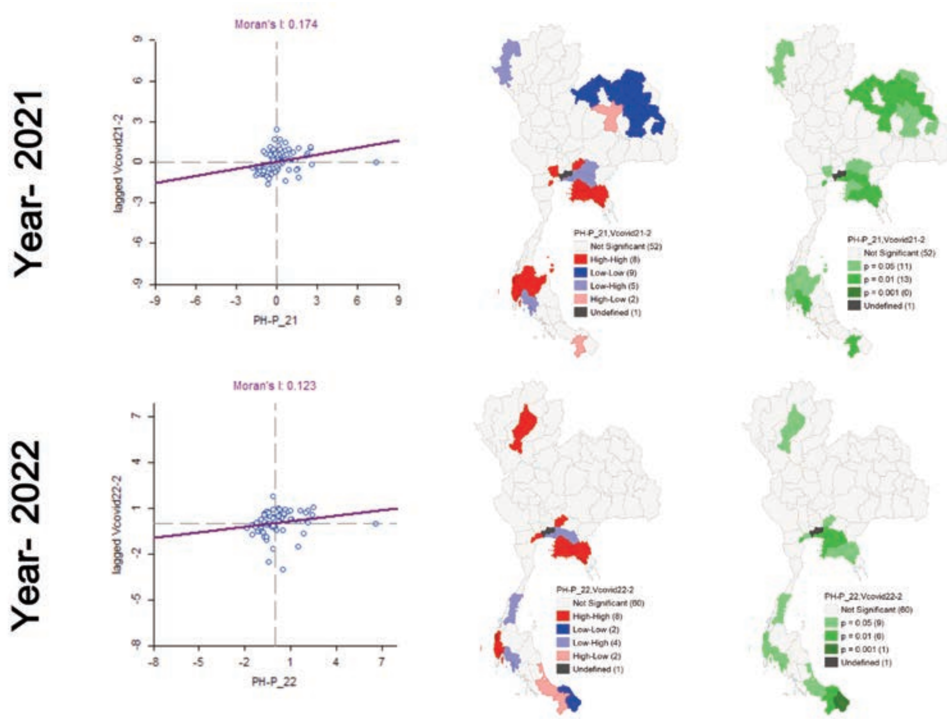

Figure 5. Levels of correlation between medical personnel and COVID-19 vaccine coverage in Thailand.

tion alone does not confirm causation, spatial autocorrelation analysis provides stronger evidence of systematic spatial patterns that influence vaccine coverage. The statistical significance of Moran's *I* and LISA results indicates that vaccine uptake is not randomly distributed but follows structured spatial dependencies shaped by socio-economic and healthcare factors. These findings reinforce the necessity of geographically targeted public health strategies to address vaccine accessibility gaps effectively. It provides an overview of the provincial structure without specifying individual factors. The application of weighted matrices with neighbouring provinces to analyse spatial correlations could explain that indirect factors influenced vaccine coverage.

Conclusions

The analysis identified positive spatial associations with COVID-19 vaccine coverage in Thailand, influenced by the epidemic, the socio-economic, and health services factors. In the first year (2021) of vaccination, limited supplies led to prioritised distribution to high-outbreak areas to control spread and reduce mortality. In high-prevalence areas, public awareness of vaccination was greater. Economically developed regions (indicated by NTL levels) had higher coverage due to greater financial resources, better access to information and efficient transport. Areas with more healthcare workers ensured rapid vaccine administration. By 2022, vaccine supply was sufficient, with diverse options available. Online systems facilitated decision-making and reservations, while vaccinations were widely accessible through public and private providers, particularly for vulnerable groups. Regions with a high number of medical personnel delivered vaccinations more efficiently. Urban areas with economic growth areas, tourist attractions, industrial areas and healthcare saw increased coverage driven by government policies linking vaccination to return to normal life.

Recommendations

The study findings could serve as evidence for any sector involved in implementing policies. They could be utilised in the organisation of annual immunisation campaigns by outlining strategies and policies appropriate for the local population in each area. Particularly in provinces located in the Northeast, where there was a shortage of medical personnel. Allocation of additional personnel and medical resources should alleviate this problem and help address concerns regarding the supply of COVID-19 vaccines. At the local level, the situation should be regularly monitored to raise awareness about self-protection, caution and avoidance of outbreak areas. COVID-19 vaccination campaignsshould be conducted for individuals who have not yet been vaccinated and those seeking an additional dose to boost the immunity. This should be carried out alongside raising health literacy and awareness among the public. Furthermore, multiple accessible avenues should be available for individuals to obtain the vaccine. COVID-19 vaccination services should be offered in multiple formats to ensure accessibility. To overcome infrastructure and transport barriers, especially in areas with low NTL, proactive services should prioritise mobile units and target isolated communities to improve healthcare access. Meanwhile, reactive services should remain available for the general public, allowing individuals to seek vaccination independently. To support informed decision-making and alleviate concerns, diverse vaccine options should be provided.

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