Spatial Association Patterns with Cultural and Behaviour with the Situations of COVID-19

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Abstract

This study is a cross-sectional study. The study of spatial association patterns and the influences on the Coronavirus Disease 2019 (COVID-19) epidemic situation in Thailand was determined using secondary data from the COVID-19 interactive dashboard, Department of Disease Control, Ministry of Public Health, between January 1st, 2020, and December 31st, 2021. Moran's I, Local Indicators of Spatial Association (LISA), and Spatial Regression was applied for statistical analysis. In the epidemic situation of COVID-19, the highest of 11,512.65 per one hundred thousand population, and the spatial association between the nighttime light average, the prevalence of smokers in Thailand, the proportion of population per village health volunteer, and the proportion of population per health care center with the epidemic situation of COVID-19 has Moran's I = 0.309, 0.396, 0.081 and 0.424, respectively. From the Spatial Lag Model (SLM), a factor that has a spatial association with the epidemic situation of COVID-19 is the nighttime light average, the prevalence of smokers in Thailand, and the proportion of population per healthcare center, which can predict the epidemic situation of COVID-19 by 47.8 percent (R^2 =0.478). The growth factor of a large city is an important factor for population density which is a major cause of spread of the coronavirus easily. Moreover, smoking behavior has encouraged the epidemic to spread rapidly. The situation is serious as the number of hospitals is not enough to support the treatment and screening of patients to cover the entire population of Thailand. Therefore, it is urgent that the government plan to mitigate the situation with maximum efficiency by having COVID-19 centers and increase the number of beds and facilities.

Keywords: Coronavirus Disease 2019, COVID-19, Spatial Analysis, Nighttime Light Average, Smoking Behavior, Village Health Volunteer, Proportion of Population per Healthcare center

1. Introduction

The diffusion of the pandemic of Coronavirus Disease 2019 into various areas in Thailand occurred due to a lack of readiness for new infectious diseases and also a huge number of emergency calls, which makes responding very difficult. Thailand's economy is seriously affected by the rising number of Coronavirus Disease 2019 infections [1]. The pandemic situations of Coronavirus Disease 2019 in other countries are also very serious, such as Singapore 1,879,806 cases, Iraq 2,459,178 cases, Malaysia 4,821,864 cases, Indonesia 6,415,328 cases, China 7,230,178, and Vietnam 11,463,404 cases [2]. Due to cultural, traditional and religious factors, most of these countries received high damage from this pandemic from their risky lifestyle limitation, especially while "distancing" from the Coronavirus Disease 2019. Spatial factor is also a big factor to overview of how to fix the pandemic situation in terms of planning and controlling [3] and [4].

Thailand has opened the Center for the Administration of the Covid Situation due to the outbreak of the Communicable Disease Coronavirus 2019 (COVID-19) for public health emergency response, also administratively directing, controlling, and monitoring the situation. Thailand has a cumulative patient population of 2,223,435 individuals from the first patient until December 31st, 2021. It recorded the total cured 2,168,494 individuals, and deceased 21,698 individuals, which is 0.98 percent [5]. Although Thailand had policy measures to deal with the spread of the Coronavirus Disease 2019 at that time [6] and [7], the number of infected people tended to be higher.

This shows the effectiveness of the policy to control the spread of the Coronavirus Disease in 2019, partly due to the emergence of new diseases and the lack of understanding of how to prepare for a major epidemic in the country. GIS represents data in a map data format that integrates location data with its descriptive information [8]. The benefits of GIS include enhanced communication and efficiency, which contribute to enhanced management and decision-making. GIS also aids in revealing patterns, associations, and geographic context. Numerous industries use GIS to enhance policy planning and management [9]. GIS will aid in gaining a better understanding of disease distribution and control in the public health section [10]. This technology will be particularly useful during the COVID-19 pandemic [11]. The area factor plays an important role in the study of the spread of the epidemic. In particular, in the COVID-19 epidemic situation, nighttime light indicates the growth of cities and metropolitan cities with high population density according to nighttime light in each province [12]. When the population density is concentrated, it increases the likelihood that the population will be exposed to COVID-19. In addition to the risk of infection due to the population density [13]. As for health behaviors, there is another factor as well, especially smoking. In addition to promoting the spread of airborne epidemics from smoking it is also a vehicle that spreads the disease widely. This group has a higher risk of serious illness than the general population. As a result of the coronavirus disease 2019, people have lost more human resources and budget for care than normal people [14]. In which the role of healthcare in the community it is also necessary. Thailand is the only nation where village health volunteers oversee the community's health system by promoting, preventing, and supporting the work of medical personnel in light of the COVID-19 pandemic, Village health volunteers play a crucial role, particularly in patient screening and community follow-up. However, the proportion of the population that Village Health Volunteers are responsible for in each area may not be covered. according to the size and density of the population, with limited Village Health Volunteers. This is a limitation of the inadequacy of Village Health Volunteers to work in community areas [15]. In addition, the inadequacy of the hospital has a huge impact to support patients and an effective screening system in the situation of the COVID-19 epidemic in each province [16]. For that reason, the purpose of this research is to find the spatial relationship and spatial factors affecting the spread of the coronavirus disease in 2019 in order to use the study as a guideline and to support policy planning in preparing for the emerging epidemic situation in Thailand to be efficient and sustainable to reflect the development of health systems. However, there has not been a study of spatial factors in the area model or GIS in Thailand, especially those related to health factors. This study aims to determine whether the average nighttime light, the prevalence of smokers in Thailand, the proportion of the population per Village Health Volunteer, and the proportion of the population per Healthcare Center are related and can predict the 2019 spread of the coronavirus disease in Thailand.

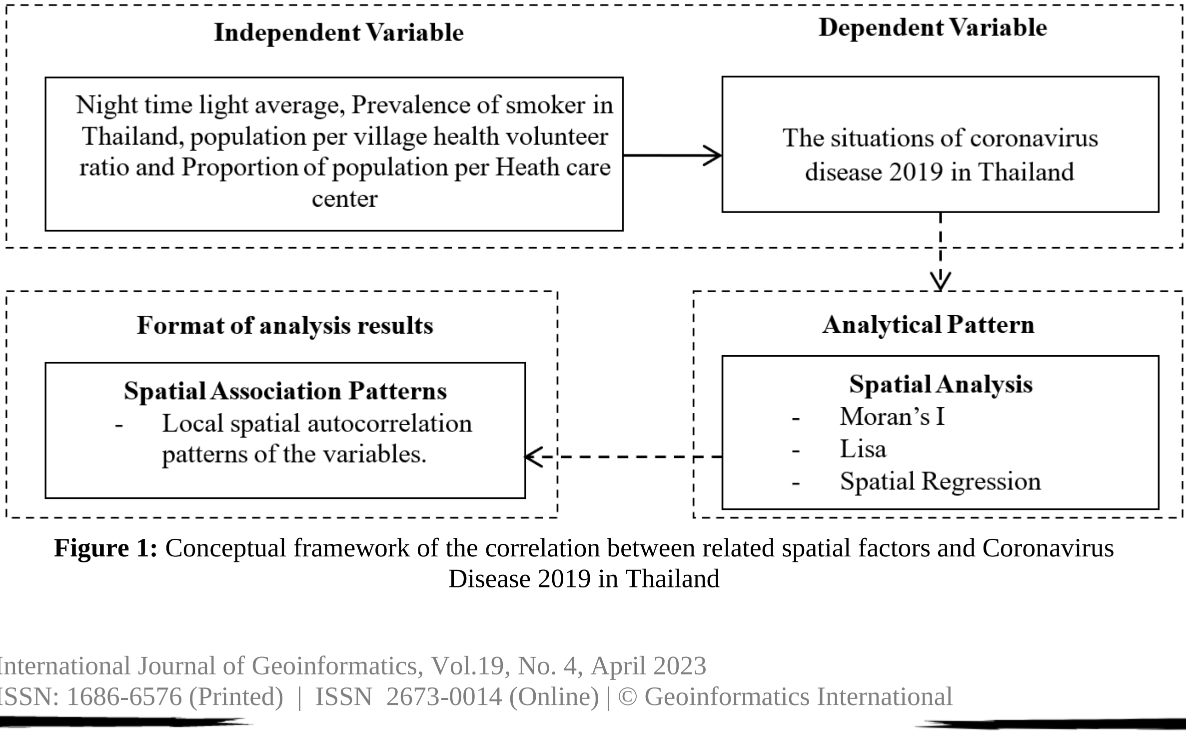

Figure 1: Conceptual framework of the correlation between related spatial factors and Coronavirus Disease 2019 in Thailand

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2. Material and Method

2.1 Study Design and Population

This spatial analysis study used secondary data from the COVID-19 interactive dashboard database, Department of Disease Control, Ministry of Public Health. The population in this study was from 77 provinces in Thailand. The sample that was included in this study was individuals who were diagnosed with COVID-19 positive between 2020-2021. When considering the inclusion criteria, the sample with complete data included in the study was 2,219,413 individuals [5].

2.2 Dependent and Independent Factors

The independent factors are nighttime light average, the prevalence of smokers in Thailand, population per village health volunteer ratio, and proportion of population per healthcare center. The dependent factor is the rate of people with COVID-19 positivity.

2.3 Statistical Analysis

The researcher used QGIS GIS package to organize spatial data [17]. Connectivity is utilized as a criterion for determining the area to indicate grouping. Utilizing the weight matrix for spatial correlation analysis [18].

Bivariate clustering and out-grouping were examined using Moran's I analysis. A Local Indicators of Spatial Association (LISA) study for any site with a significant value implies that the surrounding region is valuable if the independent variable is randomly distributed or lacks a distinct pattern within the sub-area near-independent variables. Thus, the location of the independent variable grouped both independent variables with high values (HH) and low values (LL), and vice versa. Different values of independent variables exist across the area, as shown by statistically significant discrepancies. The location with the smallest independent variable is located in the high group area (LH), and the position with the greatest independent variable is located in the low group area (HL) [19].

Correlation analysis of independent variables to build a health behavior prediction model for COVID-19 prevention. Ordinary Least Square (OLS) regression analysis was used to determine the connection, which evaluates the association without regard to the spatial relationship. In addition, the spatial lag model (SLM) and the spatial error model (SEM) were used to determine geographic statistics. Using the Coefficient of Determination (R^2), Akaike Information Criterion (AIC), and Bayesian Information Criteria (BIC), the model with the greatest R^2 and AIC-BIC values was chosen as the best regression analysis approach. Appropriate is the final model [20]. The best selection was determined from the AIC and BIC value ranges, including the maximum zero, which will have the most form this includes the best version. For example, there are some important reasons that must be complied with Paired together, they will get the most results.

3. Ethical Approval

This study was approved by the Ethics Committee in Human Research of Khon Kaen University, Khon Kaen, Thailand (HE652143).

4. Results and Discussion

4.1 Results

4.1.1 Univariates Local Indicators of Spatial Association (Univariates - LISA) between surrounding area and the situations of coronavirus 2019 in Thailand

The prevalence of coronavirus 2019 in Thailand. The province with the highest frequency is Samut Sakhon, with 11,512.65 per one hundred thousand population, while the province with the lowest frequency is Nan, with 113.13 per one hundred thousand population (Figure 2). There was a spatial correlation (Moran's I = 0.414) between the distribution pattern of the adjacent area and the same direction as the prevalence of coronavirus 2019 in Thailand. The LISA analysis indicated 14 hotspots or high-high clusters of neighboring areas and a high level of prevalence the situations of coronavirus 2019 in Thailand with also high values in the surrounding 14 provinces in Narathiwat, Yala, Pattani, Phetchaburi, Samut Sakhon, Nakhon Nayok, Chachoengsao, Chanthaburi, Chonburi, Phra Nakhon Si Ayutthaya, Pathum Thani, Nonthaburi, Samut Prakan, and Bangkok. In addition, there were 11 provinces with low neighboring areas with low levels of coronavirus 2019 in Thailand's population: Yasothon, Bueng Kan, Nakhon Phanom, Phrae, Nan, Phayao, Chiang Rai, Nakhon Sawan, Sukhothai, Phitsanulok, and Phichit.

These provinces were surrounded by three provinces with low levels of neighboring areas (cold spots or low-low clusters). And there were two provinces in Thailand with a high adjacent area and a low coronavirus situation level in 2019, in Nakhon Pathom and Samut Songkhram (low-high cluster) (Figure 3).

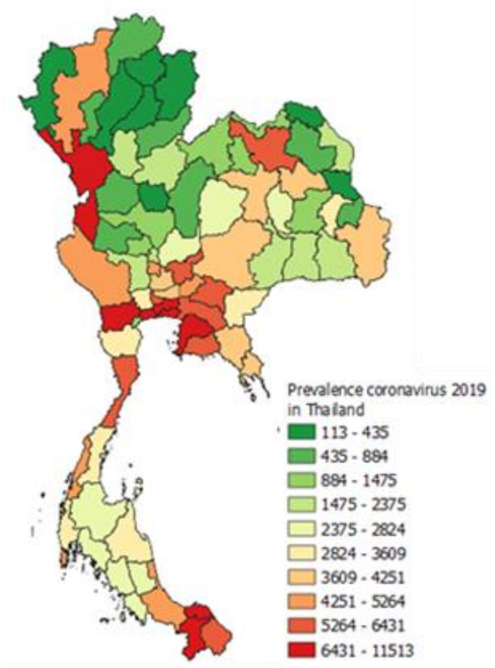
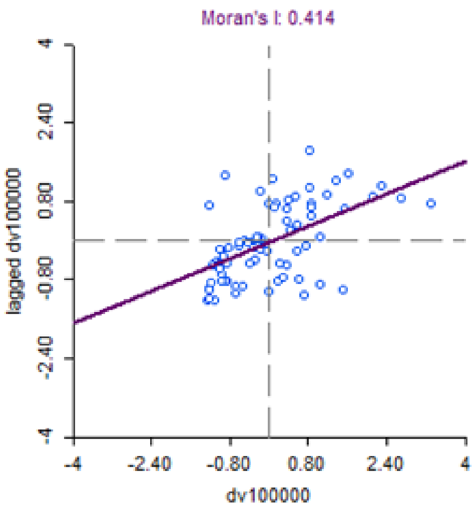
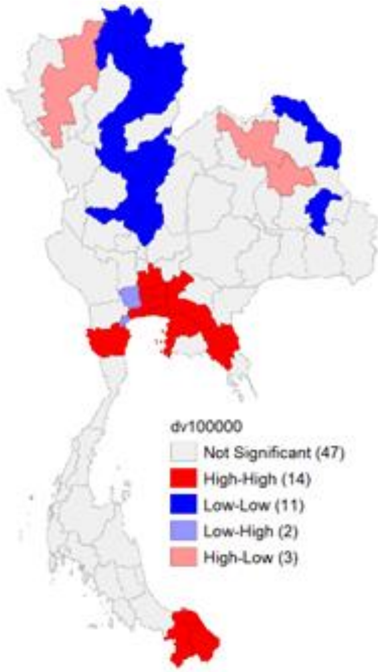


Figure 2: Decile distribution of prevalence coronavirus 2019 in Thailand



(a)



(b)

Figure 3: LISA and Moran's I scatter plot matrix of surrounding area average on COVID-2019 epidemic situation in Thailand; (a) Moran's I scatter plot matrix (Univariate: surrounding area average and COVID-2019 epidemic situation); (b) Cluster maps of surrounding area average and COVID-2019 epidemic situation

4.1.2 Spatial distribution characteristics of Coronavirus 2019 Disease in Thailand

The population in Thailand were the Coronavirus Disease 2019 infection rate 3.35%. The province of Samut Sakhon had the highest proportion, with 11,513 per one hundred thousand inhabitants, while the province of Nan had the lowest, with 113,12 per one hundred thousand inhabitants. In eight provinces, the highest deciles ranged from 6,431 to 11,513 according to the decile distribution. Samut Sakhon, Samut Prakan, Yala, Bangkok Metropolis, Chon Buri, Ratchaburi, Tak, and Pattani (Figure 4(a)). The highest decile of 4.425-20.716 percent for nighttime light average was observed in Bangkok Metropolis, Samut Prakan, Nonthaburi, Phuket, Pathum Thani, Samut Sakhon, Chon Buri and Rayong (Figure 4(b)).

The highest decile of 21.44–26.13 percent for the prevalence of smokers in Thailand was observed in Krabi, Ranong, Nakhon Si Thammarat, Satun, Surat Thani, Mukdahan, Phangnga, and Trang (Figure 4(c)). The highest decile of 124.8–522.7 for the population per village health volunteer ratio in Thailand was observed in Bangkok Metropolis, Sakon Nakhon, Kalasin, Si Sa Ket, Chiang Mai, Nakhon Ratchasima, Phuket, and Samut Prakan (Figure 4(d)). The highest decile of 12,673–20,494 for the proportion of population per healthcare center in Thailand was observed in Mae Hong Son, Chaiyaphum, Surat Thani, Ubon Ratchathani, Tak, Kanchanaburi, Chiang Mai and Nakhon Ratchasima, and (Figure 4(e)).

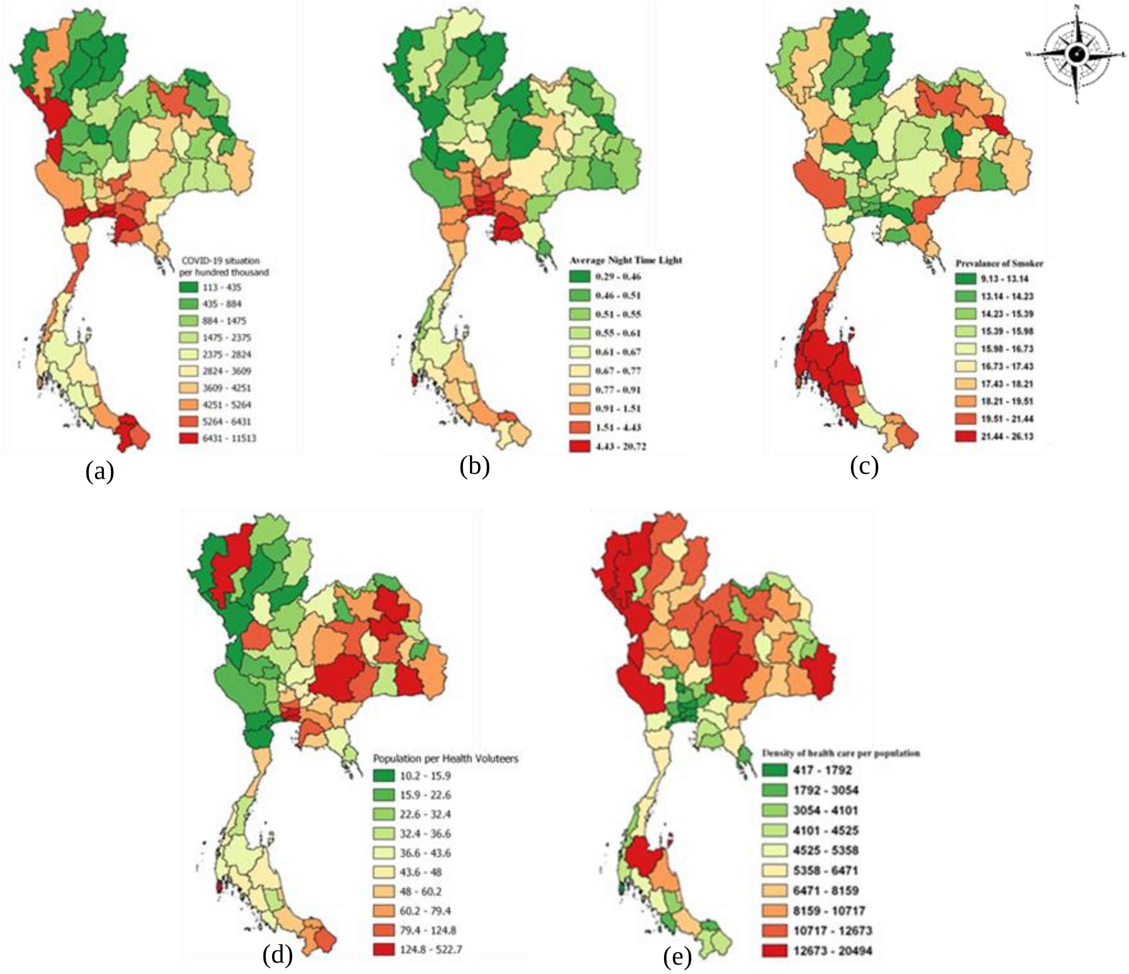


Figure 4: Decile distribution (a) Coronavirus disease 2019 infection rate (b) Nighttime light average (c) Prevalence of smoker (d) Population per village health volunteer (e) Population per healthcare center

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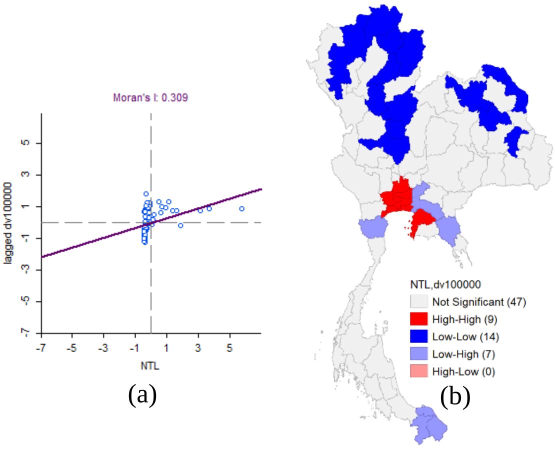
4.1.3 Local Indicators of Spatial Association (LISA) between spatial factors and the Coronavirus Disease 2019 epidemic situation in Thailand

The Moran's I test indicated statistical significance between clustering association patterns of an independent factor and the situation of the Coronavirus Disease 2019 epidemic (p-value 0.05). There was a spatial correlation (Moran's I = 0.309) between the distribution pattern of average nighttime light and the COVID-2019 epidemic situation in Thailand. The LISA analysis identified 9 hotspots or high-high clusters of nighttime light average and high level of COVID-2019 epidemic situation in Thailand, along with high values in the three surrounding provinces of Chon Buri, Phra Nakhon Si Ayutthaya, Nakhon Pathom, Bangkok, Pathum Thani, Samut Prakan, Samut Sakon, Nonthaburi, and Samut Songkhram. In addition, there were fourteen provinces exhibited low nighttime light average with low level of COVID-2019 epidemic situation in Chiang Mai, Udon Thani, Chiang Rai, Nan, Phitsanulok, Nakhon Sawan, Kalasin, Sukhothai, Phrae, Phayao, Nakhon Phanom, Phichit, Bueng Kan and Yasothon provinces encircled by low level of nighttime light in 3 neighboring provinces (cold-spot or low-low clusters). And also, there were provinces with a low nighttime light average and a high level of COVID-2019 epidemic situation, in Chanthaburi, Phetchaburi, Chachoengsao, Yala, Narathiwat, Nakhon Nayok, and Pattani, surrounded by low nighttime light averages in 3 neighboring provinces (low-high cluster) (Figure 5).

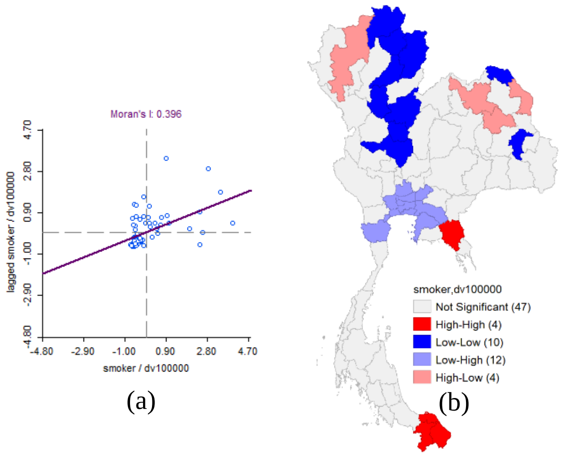
There was a spatial relationship between the pattern of distribution of smokers in Thailand relationship with COVID-2019 epidemic situation in Thailand pattern (Moran's I= 0.396). The LISA testing revealed four hotspots or high-high concentrations of the prevalence of smokers and high levels of the COVID-2019 epidemic in Thailand with also high values in the surrounding 3 provinces in Chanthaburi, Yala, Narathiwat and Pattani Provinces. In addition, 14 provinces had a low prevalence of smokers and a low COVID-2019 epidemic situation in Chiang Rai, Nan, Phitsanulok, Nakhon Sawan, Sukhothai, Phrae, Phayao, Phichit, Bueng Kan and Yasothon provinces surrounded by low level of prevalence of smoker in three neighboring provinces (cold-spot or low-low clusters). And also, there were also provinces with a low proportion of smokers and high levels of COVID-2019 epidemic situation in Phetchaburi, Chachoengsao, Chon Buri, Nakhon Pathom, Phra Nakhon Si Ayutthaya, Bangkok, Nakhon Nayok, Samut Prakan, Pathum Thani, Samut Sakhon, Samut Songkhram and Nonthaburi province surrounded by three provinces with a low prevalence of smoking (low-high cluster). In contrast, LISA analysis revealed clusters of low-density provinces of prevalence of smoker and COVID-2019 epidemic situation with also low values of surrounding 3 provinces (high-low clusters). Three low-low clusters were observed in Chiang Mai, Udon Thani, Kalasin, and Nakhon Phanom provinces (Figure 6).

There was a spatial relationship between the proportion of the population per Village Health Volunteer and its distribution pattern in Thailand relationship with COVID-2019 epidemic situation in Thailand (Moran's I = 0.081).



(a) (b)

Figure 5: LISA and Moran's I scatter plot matrix of nighttime light average on COVID-2019 epidemic situation in Thailand
(a) Moran's I scatter plot (b) Cluster map



(a) (b)

Figure 6: LISA and Moran's I scatter plot matrix of prevalence of smoker in Thailand on COVID-2019 epidemic situation in Thailand
(a) Moran's I scatter plot matrix; (b) Cluster map

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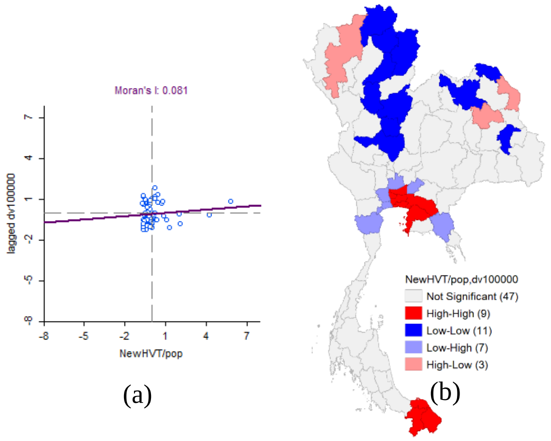

Figure 7: LISA and Moran's I scatter plot matrix of proportion of population per Village Health Volunteer in Thailand on COVID-2019
(a) Moran's I scatter plot (b) Cluster map

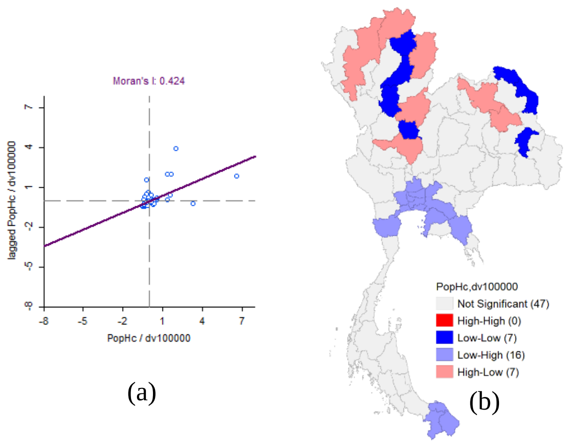

Figure 8: LISA and Moran's I scatter plot matrix of proportion of population per healthcare center in Thailand on COVID-2019
(a) Moran's I scatter plot (b) Cluster map

The LISA analysis revealed nine hotspots or high-high concentrations of population per Village Health Volunteer and high level of COVID-2019 epidemic situation in Thailand with significant values in the three neighboring provinces in Chachoengsao, Yala, Narathiwat, Chon Buri, Pattani, Bangkok Metropolis, Pathum Thani, Samut Prakan and Nonthaburi provinces, eleven provinces had a low proportion of residents per Village Health Volunteer with low level of COVID-2019 epidemic situation in Udon Thani, Chiang Rai, Nan, Phitsanulok, Nakhon Sawan, Sukhothai, Phrae, Phayao, Phichit, Bueng Kan and Yasothon provinces in three neighboring provinces, the proportion of residents per Village Health Volunteer is low (cold-spot or low-low clusters). In addition, there were provinces with a low population per Village Health Volunteer ratio and a high level of the COVID-2019 epidemic situation, in Chanthaburi, Nakhon Nayok, Phetchaburi, Nakhon Pathom, Phra Nakhon Si Ayutthaya, Samut Sakhon, and Samut Songkhram, surrounded by three neighboring provinces with low proportions of population per Village Health Volunteer (low-high cluster). In contrast, the LISA analysis revealed clusters of a province with a low concentration of the proportion of population per Village Health Volunteer and COVID-2019 epidemic situation, as well as clusters of three neighboring provinces with similarly low values (high-low clusters). Three low-low concentrations were discovered in the provinces of Chiang Mai, Kalasin, and Nakhon Phanom (Figure 7).

There was a spatial relationship between the proportion of the population per healthcare center in Thailand and its distribution pattern with COVID-2019 epidemic situation in Thailand (Moran's I = 0.424). The LISA analysis revealed seven cold spots or low-low concentrations of the proportion of population per healthcare center and the low level of COVID-2019 epidemic situation in Thailand, along with high values in the three neighboring provinces: Sukhothai, Phrae, Phayao, Nakhon Phanom, Phichit, Bueng Kan and Yasothon provinces. In addition, there were provinces with a low population per healthcare center and a high incidence of the COVID-2019 epidemic in Chanthaburi, Phetchaburi, Phra Nakhon Si Ayutthaya, Chachoengsao, Yala, Narathiwat, Chon Buri, Samut Prakan, Bangkok, Nakhon Pathom, Samut Prakan, Pathum Thani, Nakhon Nayok, Pattani, Samut Sakhon, Nonthaburi, and Samut Songkhram provinces were surrounded by provinces with three neighboring provinces with a low proportion of population per healthcare center (low-high cluster). In contrast, the LISA analysis revealed clusters of a province with a low concentration of proportion of population per health care center and COVID-2019 epidemic situation with similarly low values in the seven neighboring provinces (high-low clusters). There were discovered to be three low-low clusters in Chiang Mai, Udon Thani, Chiang Rai, Nan, Phitsanulok, Nakhon Sawan, and Kalasin provinces (Figure 8) and describe the details in tabular form in Table 1.

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Table 1: Local Indicators of Spatial Association (LISA) between spatial factors and the Coronavirus Disease 2019 epidemic situation in Thailand

Factor	LISA			
	High-High	High-Low	Low-High	Low-Low
Nighttime light	Bangkok, Samut Prakan, Nonthaburi, Pathum Thani, Phra Nakhon Si Ayutthaya, Chonburi, Nakhon Pathom, Samut Sakhon, Samut Songkhram	-	Chanthaburi, Chachoengsao, Nakhon Nayok, Phetchaburi, Pattani, Yala, Narathiwat	Yasothon, Bueng Kan, Udon Thani, Kalasin, Nakhon Phanom, Chiang Mai, Phrae, Nan, Phayao, Chiang Rai, Nakhon Sawan, Sukhothai, Phitsanulok, Phichit
Prevalence of smoker	Chanthaburi, Pattani, Yala, Narathiwat	Samut Songkhram, Chiang Mai, Phetchabun, Nakhon Ratchasima, Buriram, Surin, Ubon Ratchathani, Bueng Kan, Nong Bua Lamphu, Khon Kaen	Bangkok, Samut Prakan, Nonthaburi, Pathum Thani, Ayutthaya, Chonburi, Chachoengsao, Nakhon Nayok, Roi Et, Kalasin, Sakon Nakhon, Nakhon Phanom	Uttaradit, Mae Hong Son, Uthai Thani, Tak
Proportion of population per Village Health Volunteer	Bangkok, Samut Prakan, Nonthaburi, Chonburi, Pathum Thani, Narathiwat, Yala, Pattani, Chachoengsao	Kalasin, Chiang Mai, Nakhon Phanom	Phra Nakhon Si Ayutthaya, Nakhon Nayok, Chanthaburi, Nakhon Pathom, Phetchaburi, Samut Songkhram, Samut Sakhon	Udon Thani, Yasothon, Sukhothai, Phichit, Nakhon Sawan, Nan, Phitsanulok, Chiang Rai, Bueng Kan, Phrae, Phayao
Proportion of population per healthcare center	-	Udon Thani, Kalasin, Chiang Mai, Nan, Chiang Rai, Nakhon Sawan, Phitsanulok	Bangkok, Samut Prakan, Nonthaburi, Pathum Thani, Phra Nakhon Si Ayutthaya, Chonburi, Chanthaburi, Chachoengsao, Nakhon Nayok, Nakhon Pathom, Samut Sakhon, Samut Songkhram, Phetchaburi, Pattani, Yala, Narathiwat	Yasothon, Bueng Kan, Nakhon Phanom, Phrae, Phayao, Sukhothai, Phichit

4.1.4 Model performances of OLS, SLM and SEM relationship of spatial association patterns with the situations of Coronavirus Disease 2019 in Thailand

Determining whether the non-spatial model possessed spatial relationships and heterogeneity was the first step in constructing a spatial regression model. The Moran's I analysis revealed significant results; thus, spatial dependencies existed, signifying that each province had a close relationship with its neighbor. This relationship will be investigated in greater depth as spatial regression modeling advances.

Based on OLS, SLM, and SEM (Table 2), the Lagrange multiplier error revealed a statistically significant result, indicating that the model of spatial error is more applicable. After the spatial model had been defined, it was necessary to estimate its parameters. The table below displays the estimated model parameters for the specified model parameter, namely the spatial error model. The OLS method's parameter estimates results do not account for spatial correlation within the model is an equation of linear regression.

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Table 2: Spatial regression analysis of OLS, SLM and SEM relationship of spatial association patterns with the situations of Coronavirus Disease 2019 in Thailand

Factors	OLS	Spatial Regression Analysis	
		SLM	SEM
Nighttime light	539.818	466.963	462.408
	(>0.001)***	(>0.001)***	(>0.001)***
Prevalence of smoker	207.128	179.77	186.81
	(0.01)**	(>0.001)***	(0.028)*
Proportion of population per Village Health Volunteer	-4.301	-3.812	-4.608
	(0.277)	(0.263)	(0.184)
Proportion of population per healthcare center	0.055	0.125	0.155
	(0.364)	(0.016)*	(>0.001)***
Constant	-1351.01	-2590.99	-1408.18
	(0.370)	(0.047)*	(0.370)
R-Squared	0.340	0.478	0.469
AIC	1400.09	1388.63	1389.48
BIC	1411.81	1402.69	1401.2

** Significant correlation at the p<0.05*
*** Significant correlation at the p<0.01*
**** Significant correlation at the p<0.001*

By estimating the coefficient to make the sum of squares of the error estimate the lowest possible value (the minimum sum square) and ignoring the spatial relationship (the spatial autocorrelation) to compare, we can determine if the forecasting of the scenario is accurate. At a significance level of 0.05, Coronavirus Diseases 2019 infection in Thailand revealed that fluctuating nighttime light average extension and proportion of smoking in Thailand had a significant influence on the COVID-2019 epidemic situation in Thailand. Furthermore, the parameter estimate is derived from the SEM technique, which allows the error term in spatial regression to be linked but weighted. Weighted by the distance matrix (distance matrix) to analyze the relationship between the variables, variable extensions of nighttime light average, prevalence of smokers in Thailand, and proportion of population per healthcare center were found to have a significant effect on the COVID-2019 epidemic situation in Thailand at the 0.05 level of significance.

Regarding the findings of the SLM approach, the best fit model is a way for calculating and analyzing variables that are connected. As the weight, the spatial weight matrix which is the inverse of the distance matrix is used. In the analysis that took the surrounding area into account to determine the relationship between the variables, the average nighttime light level, the prevalence of smoking in Thailand and the proportion of the population per healthcare center were found to have a significant effect on the COVID-2019 epidemic situation in Thailand at the 0.05 level of significance. At the 0.05 level of significance, the proportion of the population per Village Health Volunteer did not demonstrate a significant influence. The R^2 value of 0.478 indicates that the model's independent variables explain 47.8% of the variance in the percentage of COVID-2019 pandemic scenario in Thailand, while the remaining 52.1% is explained by factors outside the model.

5. Discussions

Nighttime Light is one of spatial factor which showing the growth of economy and provincial expansion in Thailand, and also changing of civilization, immigration, which reflex to citizen activities, traditions, cultures, economy growth, and cities expansion. The result show in form of the average of light intensity in the nighttime and county map [12]. From the previous result, which according to Thailand situations, clearly present that growth economy cities are more pandemic than the middle-small economy cities [13], which make the pandemic control of Coronavirus Disease 2019 are not successfully, made it turn to be the one factor to make policy draft Distancing, Mask wearing, Hand washing, Testing and Thai Chana to adjust social situations, especially social office, citizens necessary to work for their lives, refer to life quality, struggling for a living [1] [21] and [22]. Except from the topic of the light, health consciousness building is also main factor too, especially smoking behavior, and Thailand is face to this problem to fix smoking behavior of Thai people [23]. Smoking is directly cause harmful to lounge and respiratory tract, which make worse to resist the Coronavirus Disease 2019 and other chronic diseases [14] moreover, smoking is not only harm the people who smoke, but it also harms other people and social in from of second-hand smoking, the cigarette's smoke can cause skin irritation and harm lounge, decrease bodies immunity and respiratory tract, the damage is highly rising if the smoker is pandemic from Coronavirus Disease 2019 [24] and [25]. The next factor is healthcare, this factor is necessary to improve for preparing for emergency situations in Thailand. Volunteer public health in villages are in the big role to serve medical services to people in communities, and Thailand is the only one country which have the volunteer public health in villages [26] between the pandemic of Coronavirus Disease 2019, they activate for support medical personal [27]. However, the high population density in the growth cities makes citizens immigrate into big towns, which causes the problem of reaching medical services because the number of citizens is too much to handle for volunteer public health (Figure 4(d)). Especially in the pandemic situation of Coronavirus Disease 2019, which make volunteer public health get a big role in "volunteer public health proactive" in term of screen patients, tracking patients in community, check the medical supplements for protect Coronavirus Disease 2019 in each area (Ministry of Public Health, 2020). Therefore, it's necessary that the government give attention to this role, which is like an outpost position. Government agencies should adjust volunteer public health numbers to suit the numbers of people in each village [28]. In other hand, managing medical personal to take respond at hospital is important too. From the study, more hospital in province is more potential to screen people whom pandemic from Coronavirus Disease 2019 and able to cure them in time [29] and [30]. Therefore, it's necessary that government agency should give attention to develop hospital and adjust medical personal in each location enough to take care overall people, including with facing with pandemic COVID-19 which is a good chance to make new level of public health and widespread better healthcare service, and preparing for chronic disease in the future.

In this study, spatial regression statistics were used to find the best model to predict the spread of the Coronavirus Disease 2019 during the years 2020–2021, which was observed from the high R-value in the study of the best model, the best of each model. They consisted of the OLS model (no statistical assumption was involved in model control), the SLM model (peripheral area to calculate model variance), and the SEM model (the difference coefficient of each area is also calculated), and from this study, the SLM model is the best model. The factors that affect it include the average amount of light at night. The prevalence of smoking behavior and the population accountability of the healthcare unit can predict the spread of the novel Coronavirus Disease 2019 during 2020-2021 for 47.8% of the people in the above study. It is consistent with past studies, which found that the average amount of light at night indicates economic growth and urbanity of each province. The media shows the growth of that province, which leads to population density in provinces with high economic growth and causes the risk of It is easier to spread the Coronavirus Disease 2019 than in dense provinces. Underpopulation in terms of maintaining social distancing measures as a result of crowded population density, making it difficult to control collectively in terms of controlling measures and laws for disease prevention and control it's difficult because of the difference. The presence of urban communities increases the risk of controlling the spread of the coronavirus disease in 2019 is consistent with the findings of previous research studies [12] and [31], which, based on the above-mentioned population density results, indicate that another consequent factor is population density and urbanization influencing the global spread of health risk behaviors, particularly smoking behavior. In addition, smoking behavior is a threat in spreading the virus. Coronavirus Disease 2019 enters the lungs from smoking cigarettes and smoking also spreads the virus widely in the form of second-hand cigarettes, which will affect people's surroundings to be infected with Coronavirus Disease 2019 unknowingly corresponds to the population density of large cities. In addition, smoking behavior is also a problem for Thailand in proper control of smoking measures, especially the control of smoking areas, leading to the highest risk. According to the findings of previous research studies [24] and [32], the spread of the Coronavirus Disease in 2019 will be concentrated in large cities, as well as treatment, prevention, and promotion of healthy behaviors. Another important factor in preventing the spread of the coronavirus disease in 2019 is the role of the medical service in the spread situation. of various epidemics, which is in one direction of the nighttime average. It conveys the density of the population of each province, which is overcrowded and may not be enough for the hospital service unit to provide appropriate health services, including promotion, prevention, and control of the disease. Efficiently as a result, the population will be unable to begin early treatment and disease control in those infected with the coronavirus disease in 2019. Consistent with the results of past research studies [22] [30] and [33]. The three factors mentioned above are consistent in the context of the growth of being a big city that affects the use of appropriate measures and laws to regulate the behavior of individuals to prevent the 2019 epidemic, so it is absolutely necessary that the relevant agencies will recognize the importance of developing a policy that is tailored to each province's unique culture, traditions, and ways of life, and that each province's economic growth will be prioritized.

Depending on the results of this research, governments, and related agencies should revise and adopt policies that promote COVID-19 prevention and medical and public health development. Particularly, regulations that are consistent with addressing and preventing unhealthy situations promote serious and transparent preventative activities. Including a strategy to encourage the establishment of village health volunteer leaders with health knowledge and the ability to adapt their conduct to the era of globalization. That requires technology to be utilized in the medical service system that is current and capable of successfully disseminating health news, as well as promoting and growing the health system's potential. Sufficient medical facilities and medical personnel are needed for potential future emergency scenarios. Therefore, it is essential to prioritize the design of policies based on the integration that fosters inclusive learning and implementation in all areas. To execute the policy in the public sector, the private sector and both sectors can collaborate. This will result in sustained growth across all sectors for Thailand's benefit in a sustainable way.

6. Conclusion

Average nighttime light indicates economic expansion. The population density of each city contributes to spread of coronavirus disease 2019 and also indicates population activities and urban dynamics. The infection and fatality rates of the new coronavirus disease 2019 are greater in high-density metropolitan regions compared to locations with an averagely low concentration of nighttime light. Individuals who engage in smoking pose a risk to themselves as well as to others and to society. in the form of passive smoking. There will be secretions coupled with smoke or vapor dispersion, which will have an impact on others in the vicinity. In crowded or poorly ventilated settings, the COVID-19 infection may spread far from the exhalation of cigarette smoke which increases the rate of disease transmission and the risk of virus infection. especially in regions with sufficient hospitals. This will enable screening and treatment for COVID-19 in a timely manner before the symptoms become life-threateningly severe. Therefore, diverse government initiatives must be supported, integrating all sectors in the fight against the disease to increase public understanding of rigorous self-defense. In order to prevent the spread of disease, the creation of medical facilities that are efficient and adequate for the population and the promotion of non-smoking in public spaces are important aspects of society to provide emergency assistance for emerging illnesses in a thorough and effective manner. This will result in ongoing progress in every sector for Thailand's long-term prosperity.

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