Spatial Distribution Patterns of Colorectal Cancer Patients in Thailand

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Abstract

Colorectal cancer (CRC) is among the leading causes of cancer-related morbidity and mortality worldwide, and it poses a growing public health challenge in Thailand, being the third most prevalent cancer in men and the fourth in women. This study aims to analyze the spatial distribution patterns of CRC cases across Thailand's 77 provinces and explore their correlation with six influencing factors: annual nighttime light (ANTL), smoking behavior, alcohol consumption, processed food consumption, vegetation avoidance, and lack of exercise. Geographic information system (GIS) techniques, cluster analysis, and l regression models, including the Ordinary least Square (OLS), Spatial Lag Model (SLM) and Spatial Error Model (SEM), were employed to uncover these patterns and relationships. The findings reveal substantial clustering of CRC cases in urbanized areas such as Bangkok and surrounding provinces, where high ANTL reflects elevated urbanization, infrastructure, and economic activity. Behavioral factors, including smoking and alcohol consumption, exhibited significant spatial clustering, predominantly in the southern and northeastern regions, respectively. The northeastern region also exhibited hotspots of processed food consumption, while vegetation avoidance rates were notably low across Thailand, reflecting widespread adherence to vegetable-rich diets. Regression analysis highlighted ANTL as the most statistically significant predictor of CRC incidence, underscoring the influence of urbanization and associated lifestyle changes on CRC rates. These results underscore the need for tailored public health interventions that account for the unique spatial dynamics of CRC risk factors. By integrating GIS tools and spatial analysis, public health strategies can target high-risk areas, optimize resource allocation, and promote region-specific lifestyle modifications, thereby improving CRC prevention and outcomes in Thailand.

Keywords: Cluster Analysis, Colorectal Cancer, Moran's I, Nighttime Light, Spatial Regression Model

1. Introduction

Colorectal cancer (CRC) is one of the leading causes of cancer-related morbidity and mortality globally, with its incidence on the rise in both developed and developing countries. According to the Global Cancer Observatory, CRC is the third most common cancer worldwide. In Thailand, colorectal cancer (CRC) presents a significant healthcare challenge as the third most common cancer in men and fourth in women, accounting for 11% of the nation's cancer burden. Notably, CRC is the only malignancy in the country with a rising incidence in both sexes. Contributing factors include a lack of organized screening programs, limited public awareness, and insufficient medical resources, with only 69 practicing board-certified colorectal surgeons for a population of 70 million. The majority of CRC cases in Thailand are diagnosed at advanced stages, which exacerbates the challenges of effective treatment [1].

Nowadays, GIS is widely used in medicine, especially in epidemiological and spatial studies [2], as well as in managing policies and laws tailored to different areas with varying contexts [3]. A geographic information system (GIS) represents data in a map format that integrates location data with its descriptive information [4]. The benefits of GIS include improvements in communication and efficiency, leading to better management and decision-making [5][6][7][8] and [9]. GIS also helps reveal patterns, relationships, and geographic context [10] and [11]. Many industries use GIS to improve policy planning and management [12]. The public health sector is one area where GIS can enhance the understanding of disease distribution and control [13][14][15][16] and [17].

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The study of spatial distribution patterns of colorectal cancer (CRC) patients in Thailand is essential for understanding the geographic variations in disease incidence and identifying factors that contribute to higher or lower rates of CRC across regions. GIS techniques, including cluster analysis and spatial correlation models [10], are crucial tools in this process, offering valuable insights into the spatial dynamics of CRC. These techniques help identify geographic areas with higher concentrations of CRC cases, which can be linked to factors such as alcohol consumption, smoking, dietary, and exercise behaviors. Mapping these patterns is key for informing targeted public health strategies, optimizing resource allocation, and improving early detection and prevention efforts.

Cluster analysis using GIS is particularly important for detecting hotspots of CRC, helping to pinpoint regions where interventions like screening programs and awareness campaigns are most needed. By identifying these spatial clusters, the areas with disproportionately high rates of the disease can be focused to ensure that resources are efficiently distributed. In addition, spatial correlation models such as the Spatial Lag Model (SLM) and Spatial Error Model (SEM) are valuable for assessing spatial dependencies in CRC incidence and influencing factors. These models account for the influence of neighboring regions on CRC rates, providing a clearer understanding of how influencing factors in one area may affect those in adjacent areas. Furthermore, regression models incorporating spatial data can be utilized to quantify the relationship between CRC incidence and various spatially-varying factors such as alcohol consumption, smoking, dietary, and exercise behaviors, as well as socio-economic factor as nighttime light. These models help identify specific risk factors that may vary by region, guiding more effective, region-specific interventions [10]. By integrating these advanced GIS techniques, the spatial distribution of CRC in Thailand and spatial distribution patterns of the CRC and the influencing factors can be investigated.

This study aims to investigate the spatial distribution patterns of CRC patients in Thailand. By analyzing geographic correlations and identifying high-incidence areas, this research will provide a foundation for evidence-based policy-making and targeted interventions. Ultimately, this study seeks to improve CRC management and outcomes by promoting equity in healthcare services and addressing the challenges posed by the rising burden of colorectal cancer in Thailand.

2. Study Area

Thailand is located in Southeast Asia between the longitudes of 97°25′E to 105°30′E and the latitudes of 5°50′N to 20°20′N, bordered by Myanmar to the northwest, Laos to the northeast, Cambodia to the southeast, and Malaysia to the south. It has a diverse geography that includes mountain ranges in the north, vast plains in the central region, and tropical beaches along the southern peninsula (See Figure 1(a)). The country is divided into 6 regions namely central, north, northeast, east, west, and south. The total area of the country is approximately 513,115 km^2 [18]. The unique geographical setting, combined with its varied climates and urban-rural divides, contributes to significant regional differences in lifestyle, healthcare access, and environmental factors, all of which can influence the spatial distribution of diseases like colorectal cancer (CRC).

The population number of Thailand in 2024 is around 71.7 millions [19], Figure 1b illustrates the population distribution across the provinces of Thailand, where the color intensity corresponds to the population size. Darker shades such as Bangkok, Chonburi, Chiangmai, and Nakhonratchasima indicate the highest population numbers, while lighter shades denote regions with smaller populations.

The diversity in Thailand's geography is reflected in the distribution of CRC cases across the country. Urban areas, such as Bangkok, tend to have higher healthcare access, better screening programs, and more advanced medical facilities, which can influence the early detection and diagnosis of CRC. In contrast, rural regions may face challenges such as limited access to healthcare, lower levels of health education, and higher rates of risk factors like poor diet and lack of exercise. These geographical disparities make it crucial to analyze CRC incidence through a spatial lens, identifying patterns that could be linked to regional differences in lifestyle, socioeconomic status, environmental exposures, and healthcare infrastructure. The geographical characteristics of Thailand, including the distinction between urban and rural environments and differences in lifestyle behaviors, significantly influence CRC rates. Urban areas often report higher CRC rates, likely due to lifestyle factors such as diets high in processed foods and sedentary habits. In contrast, rural areas may experience lower CRC rates but face significant challenges related to early detection and access to treatment.

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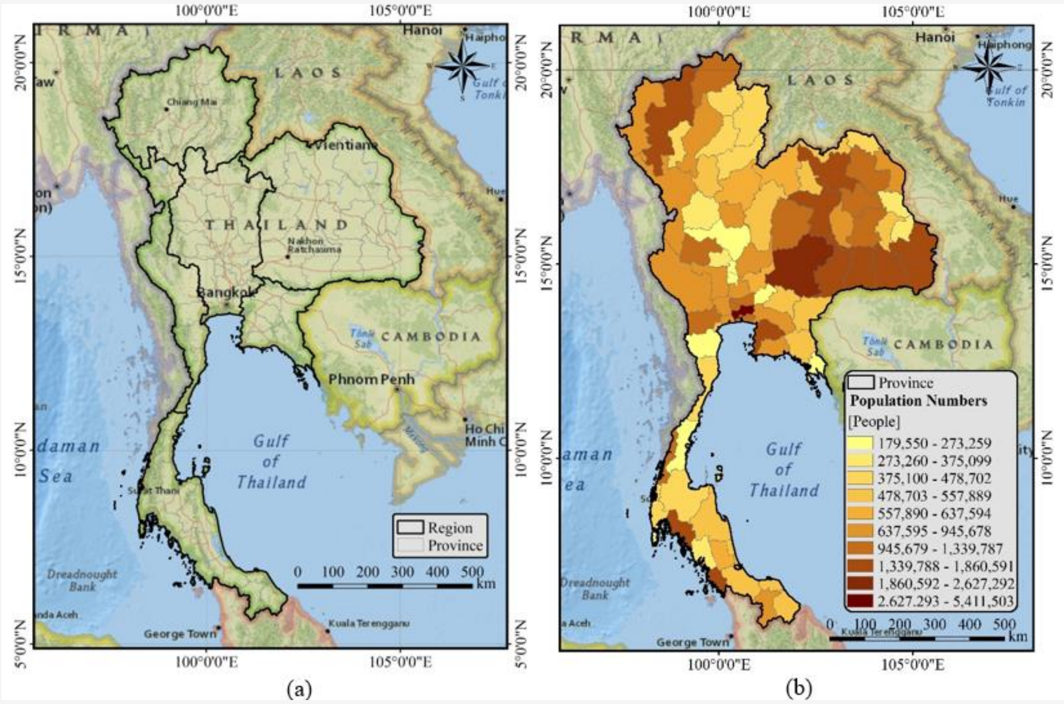

Figure 1: Thailand (a) geographical location (b) population numbers

Mapping the spatial distribution of CRC cases across Thailand can help identify high-risk areas, enhance understanding of the contributing factors, and enable the development of targeted interventions tailored to the specific needs of each region. This approach holds the potential to improve public health outcomes and reduce the overall burden of CRC in the country.

3. Materials and Methodology

3.1 Data Collections

3.1.1 CRC patients and influencing factors

This spatial analysis study utilized secondary data from the Ministry of Public Health, focusing on the population across all 77 provinces in Thailand. The study assessed all new cases of colorectal cancer (CRC) registered in the Ministry of Public Health's population-based cancer registry in 2022, classified according to the International Classification of Diseases for Oncology (ICD-O, third edition), covering codes C18.0 for the cecum to C20.0 for the rectum. This was a cross-sectional study, which included a total of 22,534 participants. The influencing factors data were also collected from the CRC patients. Lifestyle factors, including smoking, alcohol consumption, dietary habits (such as vegetable and processed food intake), and physical activity levels, were collected through questionnaires and interviews. Socio-economic data, specifically the annual Nighttime Lights (NTL) value for 2022, was obtained from the website https://eogdata.mines.edu/nighttime_light/annual/v22/2022/.

3.2 Study Work Flow

The spatial analyses in this study include cluster analysis using Global Moran's I and Local Indicators of Spatial Association (LISA). To investigate the correlations between colorectal cancer (CRC) and influencing factors, regression models such as Ordinary Least Squares (OLS) and spatial regression models, including the Spatial Lag Model (SLM) and Spatial Error Model (SEM), were employed. The methodology of the study is illustrated in Figure 2. To model the prevalence of colorectal cancer (CRC) based on various influencing factors, an initial analysis of spatial autocorrelation is crucial. Global Moran's I was used to assess the presence of spatial autocorrelation within the dataset, which includes the CRC patient numbers across all provinces in Thailand. Global Moran's I was utilized to determine whether clusters such as hotspots and cold spots exist within the dataset. If spatial autocorrelation is detected, it indicates the presence of clustering within the study area. Following this, bivariate Local Moran's I (LISA) is applied to identify local clusters and examine spatial correlations between CRC and independent variables, including behavioral factors such as smoking, alcohol consumption, dietary habits, and physical activity, as well as socioeconomic factors as average NTL.

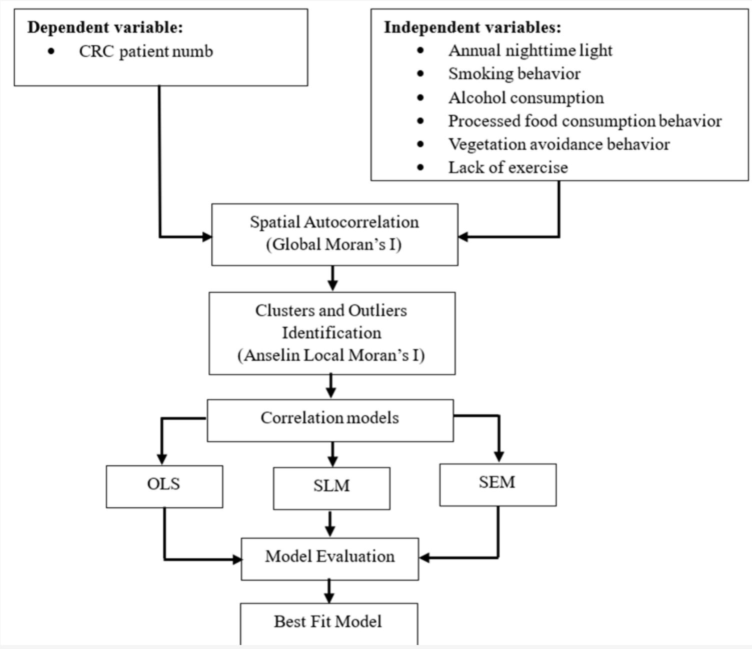

Figure 2: Spatial analysis of the CRC in Thailand methodology

Table 1: The variables used in non-spatial and spatial models

Dependent	Independent
CRC patient numbers	Annual nighttime light (ANTL)
	Smoking behavior (SMK)
	Alcohol consumption (ALC)
	Processed food consumption behavior (PFC)
	Vegetable avoidance behavior (VAB)
	Lack of exercise (EXR)

3.3 CRC Influencing Factors

The causes of CRC involve several factors. In this study, six influencing factors, as presented in Table 1, were used to model the number of CRC patients.

3.3.1 Annual nighttime light

The nighttime light acquired from the VIIRS (Visible Infrared Imaging Radiometer Suite) refers to the measurement of artificial light emissions at night, typically used to assess human activity, urbanization, and socioeconomic development. VIIRS is a satellite-based instrument aboard the Suomi NPP (National Polar-orbiting Partnership) and NOAA-20 satellites, which captures high-resolution imagery of Earth's surface in the visible and infrared spectrums [20]. The VIIRS Nighttime Lights product is a valuable tool for understanding global patterns of light, particularly in urban and industrial areas, as well as rural and less-developed regions. It provides data on the intensity of light, which can be used to infer economic activity, population density, infrastructure, and other socio-economic indicators. Annual nighttime light data typically shows the mean light intensity over a year, offering insights into geographical differences in human activity, development, and even social and environmental changes. Higher nighttime light values often correspond to more developed or populated areas, while lower values may indicate rural or underdeveloped regions.

3.3.2 Smoking behavior

Smoking behavior has been strongly linked to an increased risk of CRC. Several studies have shown that the chemicals in tobacco smoke, including carcinogens, can damage the DNA in colon cells and promote the development of cancer. Smoking contributes to the formation of polyps, which are growths in the colon that can turn cancerous over time. In addition, smoking weakens the immune system, making it harder for the body to fight abnormal cells in the colon [21]. The risk of CRC is also dose-dependent, meaning the more a person smokes and the longer they smoke, the higher their risk of developing colorectal cancer.

This relationship is seen in both current and former smokers, though the risk decreases somewhat after quitting smoking. However, even long-term former smokers still have a higher risk of CRC compared to non-smokers. Smoking is a significant risk factor for colorectal cancer, largely due to the harmful effects of tobacco smoke on the colon and the body's ability to protect against cancerous changes [22].

3.3.3 Alcohol consumption

Alcohol consumption is a known risk factor for CRC, with studies showing that both the amount and frequency of alcohol intake are linked to a higher risk of developing the disease. Alcohol can contribute to CRC by causing cellular damage, promoting inflammation, and affecting the metabolism of carcinogens in the digestive system. It also interferes with the absorption of essential nutrients, which can weaken the body's ability to repair DNA and resist cancer. The risk increases with heavier drinking, particularly for those consuming three or more alcoholic drinks per day. While the exact mechanism is still being studied, the association between alcohol and CRC remains significant, with even moderate consumption linked to a slightly elevated risk [23].

3.3.4 Processed food consumption behavior

Processed food consumption is associated with an increased risk of CRC, largely due to the presence of preservatives, additives, and high levels of unhealthy fats, sugars, and sodium. These foods often contain substances like nitrates and nitrites, which, when consumed in large amounts, can be converted into carcinogenic compounds in the body. Additionally, processed foods are typically low in fiber, which plays a protective role against CRC by promoting healthy digestion and regular bowel movements [24]. Diets high in processed foods have been linked to inflammation, altered gut microbiota, and oxidative stress factors that can contribute to the development of cancerous cells in the colon. Regular and excessive consumption of processed foods, particularly red and processed meats, is considered a significant risk factor for CRC [25].

3.3.5 Lack of exercise

Lack of exercise is a significant risk factor for CRC, as physical inactivity is associated with several biological mechanisms that promote cancer development. Regular physical activity helps maintain a healthy weight, reduces inflammation, improves insulin sensitivity, and enhances immune function all of which are protective against CRC. In contrast, a sedentary lifestyle can lead to obesity, insulin resistance, and chronic inflammation, which are known to increase the risk of CRC [26]. Exercise also stimulates healthy digestion and regular bowel movements, reducing the time that potential carcinogens remain in the colon. Studies consistently show that individuals who engage in regular physical activity have a lower risk of developing CRC compared to those who are sedentary [27].

3.4 Spatial Analytical Approaches

3.4.1 Global Moran's I

Global Moran's I is used to measure spatial autocorrelation across a geographic area, helping to identify patterns of spatial distribution in a variable. Specifically, it determines whether the values of a variable are clustered, dispersed, or randomly distributed across locations. This is useful in a variety of fields, such as geography, economics, public health, and environmental studies, as it helps understanding spatial distribution patterns and make inferences about underlying processes. For example, it can be applied to study the spread of diseases, population density, economic activity, or environmental phenomena, enabling better decision-making and resource allocation. Global Moran's I is defined in Equation 1 [28].

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}(x_i - \bar{x})(x_j - \bar{x})}{W\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

Equation 1

Where:

- n is the total number of the features (77 provinces)
- $\bar{x}$ is the average of the attribute values
- x_i is the value of the feature in location i
- x_j is the value of the feature in location j
- w is the spatial weight between location i and j
- W is the sum of $w_{i,j}$ weights

The value of Global Moran's I varies from -1 to +1 for perfect dispersion and perfect clustering, respectively, with a value of 0 indicating a random spatial distribution [29].

3.4.2 Anselin Local Moran's I

Anselin Local Moran's I is a spatial statistic used to detect local patterns of spatial autocorrelation, providing insights into how a variable behaves in relation to its neighboring locations. Unlike Global Moran's I, which measures overall spatial autocorrelation, Local Moran's I identifies specific areas where the variable exhibits clustering or dispersion.

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This tool is widely used in geography, urban studies, and environmental research to better understand localized spatial patterns and make targeted interventions. Anselin Local Moran's I is determined from Equation 2 [30].

$$I_i = \frac{x_i - \bar{x}}{S_i^2} \sum_{j=1, j \neq i}^{n} w_{i,j} (x_j - \bar{x})$$

Equation 2

Where:

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^{n} (x_j - \bar{x})^2}{n-1}$$

Equation 3

Anselin Local Moran's I calculates the degree of similarity between a location and its neighbors, helping to identify areas with high values surrounded by high values (hotspot; HH)), areas with low values surrounded by low values (cold spots; LL), and areas with values that differ significantly from their neighbors (spatial outliers; as the area with low values surrounded by high values as LH and the area with hight values surrounded by low values as HL) [31].

3.5 Spatial Modelings

3.5.1 Ordinary least square

Ordinary Least Squares (OLS) is a statistical method used to estimate the relationships between a dependent variable and one or more independent variables. It works by minimizing the sum of the squared differences (residuals) between the observed values and the values predicted by the linear regression model. In other words, OLS finds the line (or hyperplane, in the case of multiple predictors) that best fits the data by reducing the error between the observed data points and the predicted values. OLS is commonly used in regression analysis to model and infer relationships between variables. The equation for OLS presents in Equation 4 [32].

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \varepsilon$$

Equation 4

Where:

y is the predicted value of the dependent variable
β_0 is the constant of the model
β_i is the coefficient of variable i
x_i is independent variable i
ε is random error in the model
n is the numbers of variables used in the model

3.5.2 Spatial lag model

A Spatial Lag Model (SLM) is a type of spatial econometric model that accounts for spatial dependence or autocorrelation by incorporating the values of a dependent variable from neighboring locations. In this model, the value of the dependent variable at a given location is influenced not only by its own characteristics but also by the values of the dependent variable at surrounding locations. This spatial interaction is captured by adding a "lag" of the dependent variable as an explanatory variable. The Spatial Lag Model is particularly useful when dealing with data that exhibits spatial spillover effects, meaning that the outcome at one location is influenced by the outcomes in neighboring areas. It is often used in fields such as economics, geography, urban studies, and environmental science to model the spread of phenomena, like economic growth, disease outbreaks, or environmental impacts. The general form of a Spatial Lag Model presents in Equation 5 [33].

$$y = \beta_0 + \lambda W_y + x\beta + \varepsilon$$

Equation 5

Where:

λ is spatial lag coefficient
W_y is spatial weight matrix
x is independent variable
β is the coefficient of variable

3.5.3 Spatial error model

A Spatial Error Model (SEM) is a type of spatial econometric model used to account for spatial dependence or autocorrelation in the error term of a regression model. Unlike the SLM, which models spatial dependence by including the dependent variable's lagged values from neighboring locations, the SEM focuses on the correlation between the errors (residuals) across spatially related units. This type of model is useful when the spatial dependence arises from unobserved factors that affect the dependent variable and cause correlated errors. In this model, the error term is assumed to follow a spatial process, meaning that the errors at one location are correlated with the errors at nearby locations. This model is appropriate when the spatial dependence is not due to direct interactions between the dependent variable values across locations but rather due to omitted spatially correlated variables that influence the outcome. SEM model is defined in Equation 6 [34].

$$y = \beta_0 + \lambda W_\varepsilon + x\beta + \xi$$

Equation 6

Where:

W_ε is spatial weight matrix of the error

λ is spatial error coefficient

ξ is error term

3.6 Model Evaluations

3.6.1 Coefficient of determination

The coefficient of determination (R^2) is a statistical measure that indicates the proportion of variance in a dependent variable that is explained by a regression model, essentially showing how well the model fits the data. It indicates the proportion of the variance in the dependent variable that is explained by the independent variables in the model. In other words, R^2 shows how well the model's predictions match the actual data. R^2 values range from 0 to 1: In general, a higher R^2 value indicates a better fit, meaning the model explains more of the variation in the outcome.

3.6.2 Akaike information criterion

The Akaike Information Criterion (AIC) is a statistical measure used to compare and evaluate different models based on their goodness of fit and complexity. It helps in selecting the best model among a set of candidate models, balancing model accuracy with parsimony (simplicity). The AIC is particularly useful for the identification of the model that best predicts the data without overfitting. A lower AIC value indicates a better model, as it suggests a good fit with fewer parameters. When comparing models, the one with the lowest AIC is generally preferred. However, AIC should be used in relative terms (comparing models) rather than as an absolute measure of fit [10].

3.6.3 Bayesian Information Criterion

The Bayesian Information Criterion (BIC), also known as the Schwarz Information Criterion (SIC), is a statistical measure used to compare different models and select the one that best balances model fit and complexity. Similar to the AIC, BIC penalizes models for having too many parameters to avoid overfitting. However, BIC applies a stronger penalty for complexity, making it more conservative when it comes to selecting models with a large number of parameters. A lower BIC value indicates a better model, similar to AIC. When comparing multiple models, the model with the lowest BIC is generally considered the best. BIC tends to favor simpler models more than AIC, particularly when the sample size is large. BIC is a tool for model selection that helps identify the most appropriate model by considering both the goodness of fit and the penalty for complexity [10].

4. Results and Discussions

4.1 Dependent and Independent Variables Spatial Distributions

4.1.1 CRC patient numbers

The number of patients is the dependent variable in this study. Patient data collected across Thailand from the Ministry of Public Health in tabular format was presented on a map to enhance the visualization of the CRC patient distribution in 2022. The spatial distribution of CRC patient numbers across Thailand in 2022 is shown in Figure 3. The figure reveals that the five provinces with the highest number of CRC patients were Bangkok, Nakhon Ratchasima, Ubon Ratchathani, Khon Kaen, and Chiang Mai. This trend indicates that higher patient numbers were concentrated in major cities, particularly Bangkok, which had the highest total. In contrast, provinces such as Mae Hong Son, Ranong, Satun, Trat, and Singburi had the lowest CRC patient numbers, likely due to their smaller populations. Overall, the distribution shows a higher concentration of CRC patients in the northeastern and some northern regions of the country.

4.1.2 Socio-economic factor: Annual nighttime light

The Earth Observation Group (EOG) Annual VIIRS Nighttime Light (NTL) refers to a dataset derived from the Visible Infrared Imaging Radiometer Suite (VIIRS) on the Suomi National Polar-orbiting Partnership (NPP) satellite. This dataset provides annual measurements of nighttime light intensity across the Earth, capturing the glow of artificial lights visible from space. It is often used for analyzing patterns of urbanization, economic activity, and population density, as well as monitoring changes in light emissions over time [35]. Figure 4(a) displays the annual nighttime light (ANTL) data from the VIIRS, which clearly shows that the highest NTL intensities are concentrated in Bangkok and its surrounding areas, as well as in Chonburi and Rayong provinces. Significant NTL intensities are also observed in major cities such as Chiang Mai, Khon Kaen, Nakhon Ratchasima, and Ubon Ratchathani. To explore the correlation between CRC patient numbers and NTL, the data in Figure 4(a) was transformed to the provincial level using the “zonal statistics tool,” summing up the NTL for each province, as shown in Figure 4(b). The transformed data reveals that Bangkok, the capital, has the highest NTL intensity, followed by Samut Prakan, Nonthaburi, Phuket, and Pathum Thani, while Mae Hong Son has the lowest NTL intensity.

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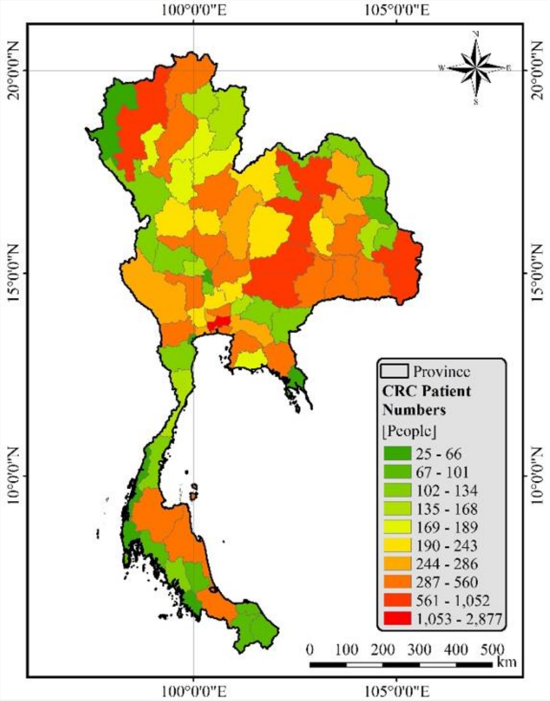

Figure 3: CRC patient numbers across Thailand in 2022

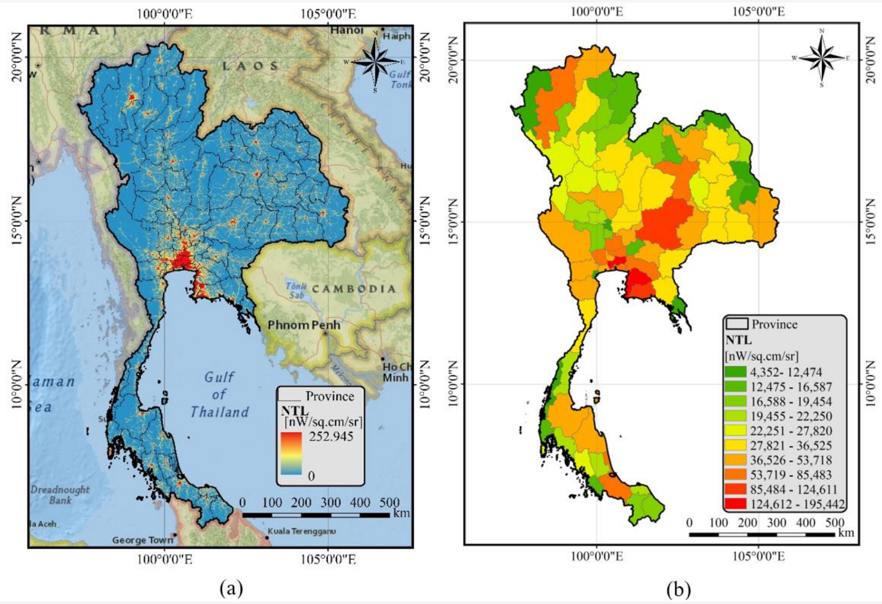

Figure 4: Annual nighttime light in 2022 (a) VIIRS NTL (b) NTL by province

4.1.3 Lifestyle behavioral factors

The percentage of each factor was calculated by comparing the ratio of the behavioral factor to the CRC patient numbers in the corresponding province. The spatial distributions of the lifestyle behavioral factor percentages are illustrated in Figure 5. The spatial distributions of the lifestyle behavioral factors can be described as follows:

Smoking Behavior (SMK): Figure 5(a) shows that the smoking rate among CRC patients ranges from 9.13% to 26.13%. The highest smoking rates are observed in the southern part of the country, which can be attributed to several factors. Culturally, smoking may be more socially accepted or prevalent in certain communities, particularly in rural or coastal regions where traditional practices influence lifestyle choices.

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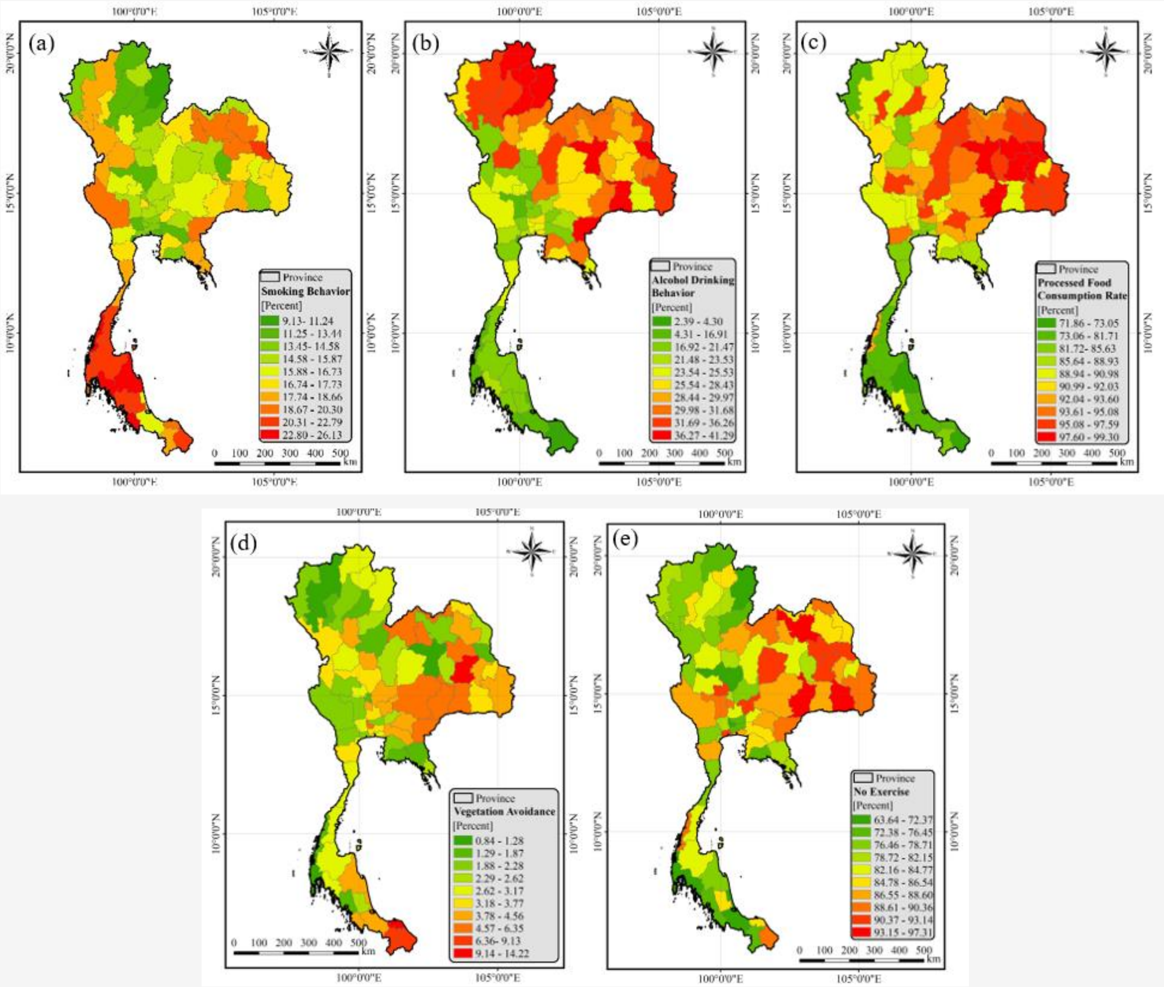

Figure 5: Spatial distribution of lifestyle behavioral factors: (a) smoking behavior (b) alcohol consumption (c) processed food consumption (d) vegetation avoidance (e) lack of exercise

In contrast, the central and some northern regions of Thailand have lower smoking rates, likely due to more effective public health campaigns and tobacco control measures, which have raised awareness about the dangers of smoking. Additionally, the central region, including Bangkok, is more urbanized, and urban areas generally experience lower smoking rates due to stricter regulations, higher education levels, and greater access to smoking cessation resources [36] and [37].

Alcohol Consumption (ALC): It is evidence in Figure 5(b) that the alcohol consumption rates are high in the northern, northeastern, and eastern parts of the country. In the northern and northeastern parts, alcohol is often a significant part of social and religious gatherings in these regions, where it is commonly consumed during festivals, ceremonies, and communal events. In rural areas, where traditional practices may have a stronger influence, drinking alcohol may be more socially accepted and even seen as a sign of hospitality. Additionally, the northern and northeastern regions have historically faced economic challenges, and alcohol consumption can sometimes be linked to coping mechanisms in response to stress, economic hardship, or limited access to healthcare. In the eastern region, alcohol consumption may be influenced by the tourism industry, where alcohol is widely promoted and consumed in leisure and entertainment settings. Moreover, public health campaigns and awareness programs in these areas may not be as widespread or effective, contributing to higher alcohol consumption rates [38] and [39]. The alcohol consumption rate is low in the central, western, and southern parts of Thailand. In the central region, including Bangkok, urbanization plays a significant role, as urban areas tend to have stricter regulations on alcohol consumption and greater awareness of its health impacts.

Higher education levels and more health-conscious lifestyles in these regions may also contribute to the lower rates. In the western and southern regions, cultural factors may play a role, with more conservative or family-oriented values that discourage excessive drinking. Religious and societal norms in these areas may promote more restrained behaviors, including lower alcohol consumption. Additionally, the southern part of Thailand, while having higher smoking rates, might have more community-focused lifestyles where alcohol use is less prevalent compared to other regions [40].

Processed Food Consumption (PFC): Figure 5(c) shows that the percentage of processed food consumption is notably high in the northeastern region and in some northern provinces, such as Lamphun and Phrae because in these region, economic factors such as lower income levels and limited access to fresh, local produce may make processed foods more affordable and accessible [41]. Additionally, processed foods often have a longer shelf life, which can be appealing in rural areas with less frequent access to markets. Convenience also plays a role, as processed foods require less preparation and cooking time, making them attractive to busy or time-constrained households [42]. In contrast, the southern part of Thailand tends to have a greater availability of fresh seafood, tropical fruits, and vegetables, which are staples in the local diet. The region's agricultural practices and coastal location contribute to a diet that relies more on fresh, locally sourced ingredients rather than processed foods. Cultural factors and traditional food practices in the south may also emphasize healthier, home-cooked meals, further reducing the reliance on processed foods.

Vegetation Avoidance (VAB): Figure 5(d) illustrates that the rate of vegetation avoidance is relatively low across the country, ranging from 0.84% to 14.22%. The low rate of vegetable avoidance across Thailand can be attributed to cultural and dietary factors.
Thai cuisine traditionally incorporates a wide variety of fresh vegetables, herbs, and leafy greens, making them an essential part of daily meals. Additionally, vegetables are widely available due to the country's rich agricultural practices, and there is growing awareness of their health benefits. The balanced diet, which often includes a mix of plant-based and animal-based foods, further encourages vegetable consumption, reducing the likelihood of avoidance. These factors collectively explain why vegetable avoidance remains relatively low across the country.

Lack of Exercise (EXR): The percentage of individuals lacking exercise in Thailand is notably high, ranging from 63.64% to 97.31% as can be seen in Figure 5(e). The high percentage of individuals lacking exercise in Thailand can be attributed to several factors, including urbanization, lifestyle changes, and cultural attitudes. In urban areas, busy work schedules, long commutes, and sedentary jobs often leave little time for physical activity. Additionally, the increasing reliance on technology and convenience has led to more sedentary leisure activities, such as watching television or using smartphones [43]. In rural areas, a lack of access to recreational spaces or facilities can also limit opportunities for exercise. Furthermore, cultural attitudes may not prioritize physical activity or fitness, contributing to lower levels of exercise across the population [44].

4.2 Spatial Autocorrelation Investigation

The Global Moran's I was used to measure the spatial autocorrelation of the dependent and independent factors. The result of the spatial autocorrelation presents in Table 2. According to Figure 2, spatial autocorrelations were observed in all the independent variables, as the p-values for these variables are below the significance level of 0.05 ($p < 0.05$). Therefore, it can be concluded that clusters of the independent variables exist within the study area. However, no clusters of CRC patient numbers were found, as the p-value for CRC is greater than 0.05, indicating that CRC patient numbers occur randomly across the country. Nevertheless, outliers in CRC data were further identified using Anselin's Local Moran's I (LISA) [45].

Table 2: Interpretation of Global Moran's I

Variables	Moran's Index	Z-score	P-value	Interpretation
CRC patient numbers (CRC)	0.022	0.638	0.52	Random
Annual nighttime light (ANTL)	0.342	4.985	0.00	Clustered
Smoking behavior (SMK)	0.559	7.458	0.00	Clustered
Alcohol consumption (ALC)	0.701	9.334	0.00	Clustered
Processed food consumptiion (PFC)	0.653	8.681	0.00	Clustered
Vegetation avoidance (VAB)	0.338	4.880	0.00	Clustered
Lack of exercise (EXR)	0.245	3.357	0.00	Clustered

4.3 Anselin Local Moran's I

The previous section confirms the presence of clusters of influencing factors. To identify the specific locations of these clusters and outliers, Anselin's Local Moran's I was applied. The results of this analysis are shown in Figures 6 and 7. The hotspot for CRC patient numbers (HH) was identified in Samut Prakarn province, which has a high number of CRC patients and is surrounded by neighboring provinces with similarly high patient numbers. The low-high outliers (LH) were found in Nakhon Pathom, Samut Sakhon, Chachoengsao, and Chaiyaphum provinces. The cold spot (LL) was observed in Narathiwat, located in the southern part of the country. No clusters or outliers were found in the northern, upper central, and western regions.

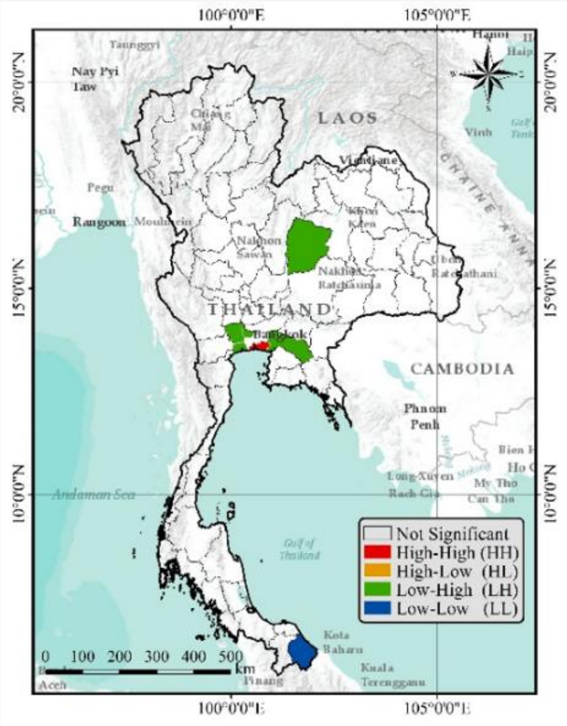

Figure 6: Cluster analysis result of CRC patient numbers

The clusters of the independent factors in Figure 7 can be summarized as follows:

Annual nighttime light: Figure 7(a) shows that high intensity of ANTL clusters in the central part of the country, especially in Bangkok and the vicinity areas (Nonthaburi, Pathumthani, Nakhon Pathom, Samut Sakorn, Samut Prakarn, Chachoengsao, and Rayong), Nighttime light intensity is clustered in the areas, due to factors such as high urbanization, economic activity, and infrastructure. Bangkok, as the capital city, has significant commercial, residential, and government sectors that contribute to elevated nighttime lighting. Rayong, an industrial hub with major manufacturing sectors, also sees increased light intensity from factories and industrial operations. Additionally, both areas have dense transportation networks and infrastructure, further driving nighttime light levels, while tourism and entertainment in Bangkok add to the lighting concentration. LH outliers were identified in Chantaburi and Nakhon Nayok provinces. It can be inferred that these two provinces have lower ANTL, whereas the surrounding provinces exhibit higher ANTL.

Smoking Behavior: Figure 7(b) shows that the hotspots were primarily concentrated in the southern part of Thailand, with the exception of Songkhla, where an LH outlier was identified. Clusters were not found in Phuket, Satun, Pattani, Yala, and Narathiwat. In contrast, cold spots were observed in several provinces in the central and northern regions, as detailed in Table 3.

Alcohol Consumption: Figure 7(c) illustrates that cold spots were primarily concentrated in the southern part of Thailand, with the exception of Phuket, Chumphon, and Nakhon Si Thammarat. LH outliers were identified in Tak and Si Sa Ket, while hotspots were observed in the northern and northeastern regions, as shown in Table 4. Additionally, clusters and outliers were not found in the central, eastern, and western parts of the country.

Processed Food Consumption: Figure 7(d) shows that the hotspots were found in Phetchabun, Lop Buri, and the entire northeastern region, with the exception of Bueng Kan and Ubon Ratchathani. Cold spots were observed in Prachuap Khiri Khan and the entire southern region, excluding Phang Nga, Chumphon, and Phuket. An HL outlier was identified in Ranong. The central region (excluding Lop Buri), northern region (excluding Phetchabun), as well as the western and eastern regions, did not show any clusters or outliers.

Vegetation Avoidance: Figure 7(e) illustrates that the spatial patterns were not observed in the central, western, and eastern regions. The LH outliers were found in Maha Sara Kham and Mukdahan in the northeastern region, while the outlier HL was found in Sukhothai. The hot spots and cold spots illustrates in Table 5.

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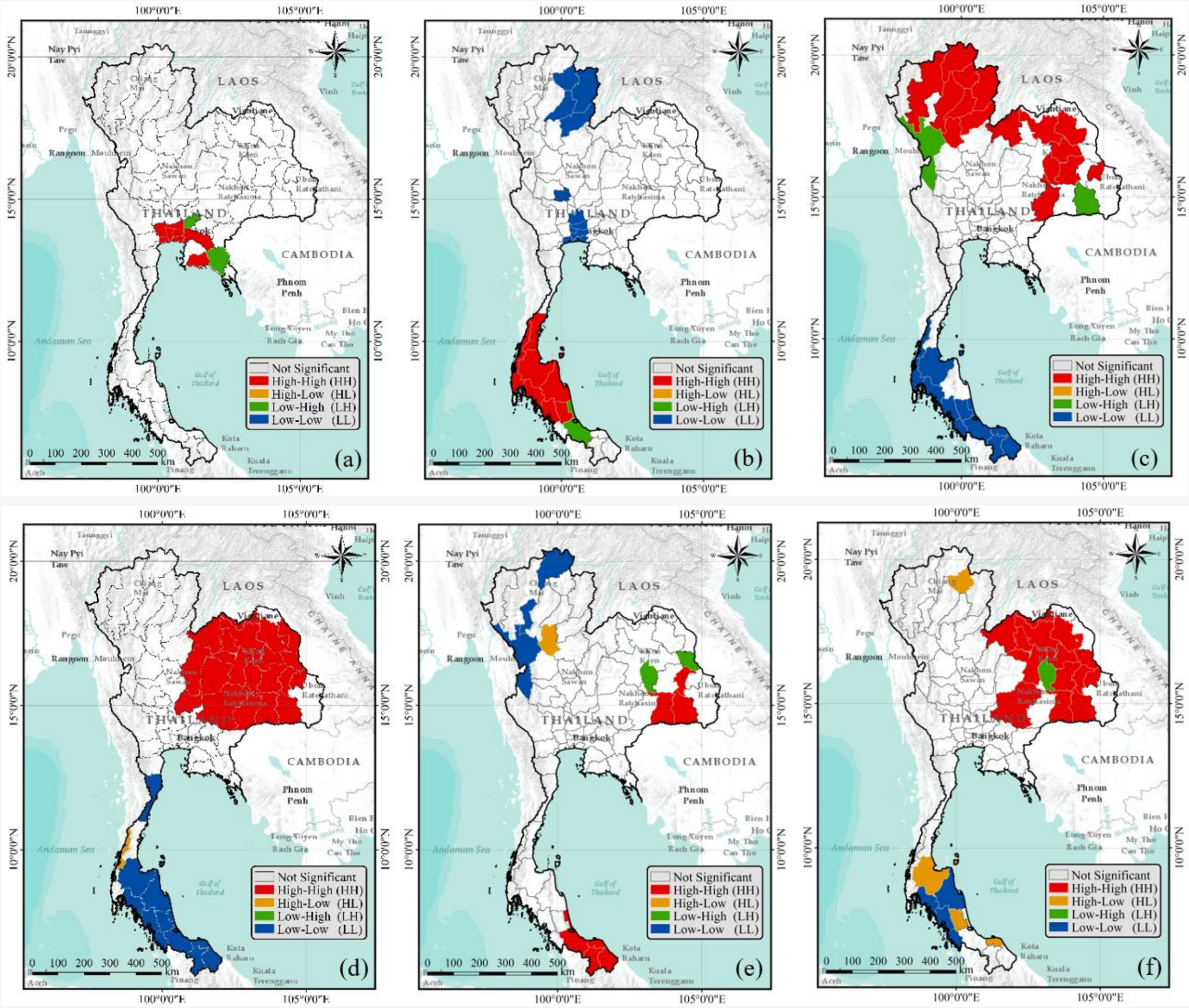

Figure 7: Cluster analysis result of independent factors (a) annual NTL (b) smoking behavior (c) alcohol consumption (d) processed food consumption (e) vegetation avoidance (f) lack of exercise

Table 3: Summarize of smoking behavior pattern

Pattern	Region	Provinces
LL	Central	Chat Nat, Phra Nakhon Si Ayutthaya, Pathumthani, Nonthaburi, Bangkok,Samut Prakan, and Samut Sakhon
	Northern	Phayao, Phrae, Uttaradit, and Nan

Table 4: Summarize of alcohol consumption pattern

Pattern	Region	Provinces
HH	Northern	Mae Hong Son, Chiang Mai, Chiang Rai, Lampang, Nan, Phayao, Phrae, and Uttaradit
	Northeastern	Loei, Udon Thani, Sakon Nakorn, kalasin, Maha Sarakham, Roi Et, Buri Ram, and Amnat Charoen

Table 5: Summarize of vegetation avoidance pattern

Pattern	Region	Provinces
HH	Northeastern	Surin, Si Sa Ket, and Yasothon
	Southern	Songkhla, Yala, Pattani, and Narathiwas
LL	Northern	Tak, Lamphun, and Chiang Rai

Lack of exercise: Figure 7(f) shows that the LH outlier was found in Maha Sarakham, while cold spots were identified in the southern part of the country, specifically in Nakhon Si Thammarat, Krabi, Trang, and Satun. HL outliers were observed in Surat Thani, Phatthalung, Pattani, and Phayao. The figure also indicates that hotspots were present only in the northeastern region, with the exception of Bueng Kan, Nakhon Phanom, Ubon Ratchathani, Maha Sarakham, Chaiyaphum, and Buri Ram. The analysis of independent factors reveals distinct spatial patterns across Thailand. Annual nighttime light (ANTL) clusters prominently in the central region, particularly in Bangkok and its surrounding provinces, due to high urbanization, economic activity, and infrastructure. Industrial hubs like Rayong also exhibit high ANTL levels, while provinces such as Chantaburi and Nakhon Nayok stand out as low outliers. Smoking behavior hotspots are mainly in the southern region, with exceptions like Songkhla, whereas cold spots are concentrated in parts of the central and northern regions.

For alcohol consumption, hotspots are prevalent in northern and northeastern provinces, while cold spots dominate the south, with some LH outliers in Tak and Si Sa Ket. Processed food consumption exhibits hotspots in Phetchabun, Lop Buri, and the northeastern region, excluding specific provinces, while the southern region has cold spots. Vegetation avoidance patterns reveal hotspots in parts of the northeastern and southern regions, with outliers noted in Sukhothai, Maha Sarakham, and Mukdahan. Lastly, lack of exercise shows cold spots in the southern provinces and hotspots primarily in the northeastern region, with distinct outliers in Maha Sarakham and Phatthalung. Each factor reflects regional variations influenced by socio-economic, cultural, and geographic conditions.

4.4 Spatial Models

The number of CRC patients and all six variables were modeled using OLS, as well as spatial regression models including SLM and SEM. The regression models and their evaluation are presented in Table 6. Table 6 shows that the most suitable model for CRC patient numbers and the influencing factors is the Spatial Lag Model (SLM), as it has the highest R^2 value of 0.598 and the lowest AIC compared to the other models. Although the BIC for the SLM is the highest, the difference is not statistically significant when compared to the other models. Additionally, the R^2 value confirms that the SLM is the best fit model. The Pearson correlation (R), derived from the R^2, is approximately 0.77, indicating a strong correlation for this model. However, when considering the p-values of all the variables, it is clear that only the p-value for ANTL is statistically significant ($p\text{-value} < 0.05$), suggesting that ANTL is the only variable that should be included in the model, while the other predictors should be excluded. However, excluding all variables except ANTL contradicts the reality, as all the variables are recognized as contributing factors to CRC. The finding that only ANTL is statistically significant in the CRC modeling using the SLM, while the other variables are not statistically significant, can be explained by several factors:

Spatial Autocorrelation of ANTL: ANTL is a proxy for urbanization, economic activity, and overall environmental factors that might influence health outcomes. In the SLM, the significance of ANTL suggests that spatial patterns of CRC are strongly related to the intensity of urban areas, where lighting typically reflects higher population density, increased access to healthcare, or environmental exposures that could influence CRC rates. The spatial autocorrelation in the SLM indicates that CRC patient numbers in one area are influenced by nearby regions with similar characteristics, which may correlate with higher ANTL.

Table 6: CRC patient numbers regression models

Variables	OLS		SLM		SEM	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constant	42.603	0.937	158.824	0.752	56.328	0.916
Annual nighttime light (ANTL)	0.008	0.000**	0.008	0.000**	0.008	0.000**
Smoking behavior (SMK)	0.715	0.942	-5.254	0.575	1.530	0.874
Alcohol consumption (ALC)	6.854	0.116	7.436	0.061	6.717	0.111
Processed food consumption (PFC)	-3.520	0.574	-4.930	0.394	-3.532	0.556
Vegetation avoidance (VAB)	13.567	0.337	13.928	0.282	12.720	0.349
Lack of exercise (EXR)	0.404	0.933	2.415	0.589	0.039	0.993
R^2	0.571		0.598		0.572	
AIC	1,070.42		1,068.27		1,070.3	
BIC	1,086.83		1,087.03		1,086.7	

Data Quality or Measurement Issues: It's possible that the data for other variables might be less accurate, incomplete, or inconsistent across regions, which could reduce their statistical significance. For instance, the behaviors related to CRC might not be fully captured by regional data, especially if individual lifestyle factors are not adequately measured or if there are reporting biases.

Insufficient Variation in Non-Significant Variables: The lack of statistical significance for lifestyle factors like smoking, alcohol consumption, and diet could also reflect insufficient variation in these variables across regions. If these factors are relatively uniform or less variable in the regions studied, their ability to explain differences in CRC incidence may be diminished, making them less likely to show a significant effect.

Confounding Factors or Interactions: It's also possible that the non-significant variables interact with other unmeasured factors that were not included in the model. For instance, socioeconomic status, access to healthcare, or genetic predispositions might interact with lifestyle behaviors in ways that are not captured in the model, thus masking the true effect of these behaviors on CRC rates.

Long-Term vs. Short-Term Exposure: Lifestyle behaviors may influence CRC over longer time frames, whereas ANTL might reflect more immediate or current environmental factors that influence the distribution of CRC cases more directly in the short term. The temporal aspect of exposure may explain why ANTL shows a stronger relationship with CRC in this model.

Model Sensitivity: The SLM is sensitive to spatial relationships, meaning that the model is more focused on capturing the spatial clustering of CRC cases. If smoking, alcohol, or other behaviors do not exhibit clear spatial patterns or clusters, they may not emerge as significant predictors within the framework of the spatial regression model. Overall, the statistical significance of ANTL in explaining CRC may be due to its role as a spatial indicator of urbanization and environmental factors, while the other behavioral variables may not exhibit clear spatial patterns or may be overshadowed by more dominant factors such as NTL or other unmeasured variables.

5. Conclusion

This study sheds light on the spatial distribution of colorectal cancer (CRC) cases in Thailand, offering valuable insights into the role of geographic and behavioral factors in influencing disease incidence. By employing GIS-based spatial analysis and regression modeling, distinct regional patterns of CRC incidence and its contributing factors have been identified, providing a basis for evidence-driven public health interventions. One of the most critical findings is the significant clustering of CRC cases in urbanized areas such as Bangkok and adjacent provinces, which correspond to high annual nighttime light (ANTL) levels. As an indicator of urbanization and economic development, ANTL reflects various lifestyle changes and environmental exposures, including increased consumption of processed foods, sedentary behavior, and higher healthcare accessibility. While urban areas exhibit higher CRC rates, they also benefit from better access to screening and diagnostic services, contributing to earlier detection and possibly higher case numbers.

The study also highlights the role of lifestyle behaviors in CRC distribution. Smoking and alcohol consumption were found to cluster significantly in the southern and northeastern regions, respectively. These findings align with cultural norms and socio-economic factors prevalent in these regions. For example, high smoking rates in the south may be attributed to traditional practices and weaker public health regulations, while alcohol hotspots in the northeast likely reflect its integration into social and religious gatherings. Processed food consumption was highest in the northeastern region, influenced by economic constraints and limited access to fresh produce. Conversely, vegetation avoidance rates were uniformly low across Thailand, reflecting the central role of vegetables in Thai cuisine.

Regression analysis further established ANTL as the most statistically significant determinant of CRC distribution, overshadowing other behavioral factors. This indicates that urbanization and its associated risk factors play a dominant role in shaping CRC patterns. However, other variables such as processed food consumption and lack of exercise, though not statistically significant in the model, remain recognized contributors to CRC risk. The non-significance of these variables could be attributed to limitations in data resolution, uniformity in behavioral patterns across regions, or confounding effects from unmeasured variables.

The implications of these findings are profound for public health policy and CRC management in Thailand. Urban areas with high ANTL require enhanced screening programs and awareness campaigns to mitigate the increasing burden of CRC. Behavioral interventions, such as anti-smoking campaigns and alcohol regulation policies, should be tailored to regions where these behaviors cluster. Moreover, efforts to promote physical activity and reduce processed food consumption in high-risk areas are essential for long-term CRC prevention.

6. Recommendation and Future Work

It is recommended that future research delve deeper into the socio-economic, genetic, and environmental factors contributing to CRC. Exploring the temporal dynamics of risk factors and their cumulative effects over time would offer a more comprehensive understanding. Integrating GIS technology in routine public health planning can provide dynamic monitoring of CRC trends, ensuring timely and effective interventions. Ultimately, by addressing regional disparities and targeting high-risk populations, public health strategies can reduce the CRC burden and improve healthcare equity across Thailand.

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