Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 2 (2024)

Association Among Environmental Factors, Economic Factors, and NCDs

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Abstract:- The study explores the relationship between environmental and economic factors and non-communicable disease (NCD) mortality in Thai provinces from 2018 to 2021. Using machine learning techniques and spatial analysis, it identifies key factors influencing NCD mortality, including air pollution, land surface temperature, nighttime light data, GDP, and population density. The random forest algorithm predicts NCD mortality with high accuracy (98–99%) and highlights the significant associations between environmental and economic factors and NCD mortality. These findings emphasize the importance of addressing environmental and economic factors in public health policy to reduce the burden of NCDs in Thailand.

Keywords*:*Non-Communicable Diseases, Thailand, Spatial Analysis, Machine Learning, Environment, Economy.

1. Introduction

Non-communicable diseases (NCDs) pose significant threats to public health in Thailand, encompassing ailments like cardiovascular diseases, cancer, chronic respiratory diseases, and diabetes. Globally, NCDs contribute to 71% of the 55.4 million deaths, occurring in individuals aged 30 to 69, predominantly in low- and middle-income countries (WHO, 2021). The informal economy, which includes workers in domestic settings and local markets, often bears the economic burden of NCDs.

Chen, Simiao, et al. (2018) [1] assessed the impact of NCDs on the United States' productivity, revealing a total loss of USD 94.9 trillion due to these diseases. The study proposed a dynamic production function model that posits three pathways through which NCDs affect the economy: direct mortality of working-age individuals reduces aggregate output; illness decreases productivity or leads to reduced working hours; and resources divert towards medical treatment and prevention. Addressing NCDs' economic implications is critical for mitigating their negative effects on individuals, society, and the national economy. Reduced illness correlates with higher productivity and economic growth at regional and national levels (Bukhman et al., 2015) [2].

Environmental factors, such as air pollution and climate change, have a significant impact on NCD mortality. Environmental factors disproportionately affect vulnerable populations, altering their dietary habits and increasing the risk of diet-related NCDs. Moreover, geographic clusters with high NCDs mortality underscore the complex interaction between environmental and socioeconomic factors. (Savage et al.,2021) [3]

The study aims to investigate the dependent factor that influences the prevalence of NCD mortality. The study uses machine learning and spatial econometric models to figure out the pattern into the NCDs area density through spatial association, which changes how the effects work in different areas. It focuses on environmental and economic factors from satellite data. Understanding these dynamics is essential for shaping public health policies and fostering economic development.

2. Related Work

To summarize the significance of these studies in context, health really affected economic growth through its impact on human capital accumulation (Bloom & Canning, 2000; Jack & Lewis, 2009) [4]. Likewise, Erdil and Yetkiner (2009) [5] examined the links between real per capita GDP and real per capita health expenditure in low- and high-income countries. The study found bidirectional and unidirectional causality between health expenditure and income. Accordingly, to bilateral causality, economic growth can also improve the health standards of the population through the purchase of healthcare (Grossman, 1972).

NCDs are health issues, particularly those that impede economic growth, as stated in the previous study. Nowadays, NCDs are emerging health issues for developing countries, and the burden of NCDs disease and risk factors is shifting toward the poor due to the long-term medical expenses associated with their care. Engelgau et al. (2011) [6] found that families living in poverty were more likely to be exposed to environmental and behavioral risk factors for NCDs. The significant determinants of NCDs are physical and biological environmental factors (Henke and Petropoulos 2013), including air pollution (Ross et al. 2013), climate change (Chen et al. 2010), hazards (Few et al. 2009), and water quality (Gu¨nther and Schipper 2013). Socioeconomic determinants strongly influence the distribution of risk factors, morbidity, and mortality of NCDs, and climate change disproportionately affects vulnerable populations who lack the resources to adequately respond (Savage et al., 2021) [3]. Moreover, Nkhasi, Maletela, and Amanda (2016) [7] identify towns with a high risk of fatalities from specific NCDs, as well as associated socioeconomic and demographic characteristics. Urban and rural areas exhibit clusters of high-risk mortality from specific NCDs. Therefore, this study will include factors related to environmental demographic characteristics.

In order to investigate the effects of the factors, the study utilized machine learning techniques to tackle the complexity of various factors. Machine learning proved invaluable in navigating through vast amounts of data, offering predictive models that are particularly effective in addressing intricate health issues with numerous determinants. Machine learning not only explains health patterns, but also predicts their distribution within communities by leveraging socio-demographic data, as highlighted by Luo et al. (2015) [8]. Bin Yu (2020) [9] also introduced machine learning to global health research by utilizing free software R program packages for geographic mapping. This approach utilizes country-specific data for population and density, demonstrating the potential of global mapping in addressing local medical and health issues of global significance.To overcome Puttanapong, N., Prasertsoong, N., and Peechapat, W. (2023) [10], introduce the integrated open data from Google Earth Engine for extracting satellite data and machine learning techniques to predict provincial GDP. The empirical validation shows that the random forest (RF) method achieves the highest predictive power with 97.7% accuracy. Other countries can use this forecast to monitor regional development. According to the factors affecting NCDs, Jain, S., and Jain, V. (2022) [11] estimate the population's shared risk factors for NCDs. A machine learning algorithm will analyze the structured data stored in the database to predict and categorize numerous diseases. If any metrics exceed a specific limit, analytics predicts the disease's risk. By using machine learning, we might be able to determine the particular variables that influence NCDs.

To study the relationship by area, this study employs spatial analysis to analyze the relationship between the significant factors related to each area. Spatial correlation analysis plays a vital role in linking non-communicable diseases (NCDs) with geographic environmental and economic factors by examining spatial patterns and relationships within a geographical context. It investigates the spatial patterns of health indicators and their associations with influencing factors (Li et al., 2024) [12] Using public health data and satellite-based environmental factors (2006–2020), Onprasonk et al. (2023) [13] looked at the spatial relationship between environmental factors and the incidence of melioidosis in Thailand. A study of two-variate local indicators of spatial association (LISA) showed that all of the satellite-based environmental factors were statistically linked to the incidence of melioidosis. The majority of the statistically significant clusters (p-value < 0.05) were found in the Northeast region. As illustrated, Nkhasi, Maletela, and Amanda (2016) [7] also explored environmental factors related to NCDs, focusing on air pollution, climate, and water quality. They identified high-risk areas for specific NCDs using spatial analysis techniques such as Moran's index and hot spot analysis, emphasizing the importance of considering geographic patterns in addressing NCDs.

3. Materials and Methods

3.1 Data

This section examines a dataset that investigate the impact of environmental and economic factors on NCD mortality, utilizing both NCD mortality data and satellite data.

A. The NCDs mortality rate

The NCD mortality rate, including diabetes, hypertension, ischemic, and chronic diseases, reveals the number of NCD-related deaths per 100,000 people between 2018 and 2021, categorized by province and health district.

B. The environmental and economic data

The study utilizes environmental and economic data, primarily sourced from satellites and surveys. Google Earth Engine is a cloud service that provides access to satellite data and computing capabilities.

Sentinel-5P measures a portion of the pollution gases, such as nitrogen dioxide (NO_2), carbon monoxide (CO), sulfur dioxide (SO_2), and methane (CH_4), with high temporal and spatial resolution. Particulate matter with a diameter less than 2.5 microns (PM 2.5) is also considered and collected daily by the Pollution Control Department.

Part of the geographic data includes land surface temperature during both day and night (daytime and nighttime), measured by MODIS, and transformed into monthly averages per province. We derive precipitation data from satellite information and station data, utilizing interpolation techniques to provide accurate estimates. Terra and Aqua MODIS reflectance data identify urban and cropped areas, generating global maps with a spatial resolution of 500 meters.

Nighttime-light data (NTL), obtained from satellites such as VIIRS and DNB, represents a portion of sociodemographic factors by indicating economic activity and socioeconomic status. The Office for National Statistics also sources the Gross Regional and Provincial Product (GPP), age, gender, and population statistics.

3.2 Methodology

This section illustrates a study framework that investigates the association between environmental and economic factors impacting NCDs in Thailand using the following processes:

Firstly, all retrieved data will be normalized by taking natural logarithms. Then, machine learning techniques will be utilized to quantify the influential factors by setting mortality of NCDs as target variables, including diabetes, hypertension, ischemic, and chronic, during the years 2018–2021, while both environmental factors and economic factors were set as explanatory variables.

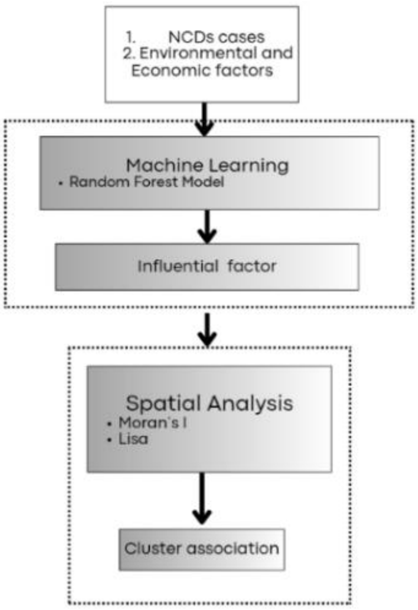


Figure 1: Analysis Framework.

Finally, spatial analysis e.g., Local Indicator of Spatial Association: LISA will be applied for mapping the influence factors by colored map clustering as presented in Figure 1.

A. Identify influencing factors through machine learning.

Along with the expanding public access to satellite data and machine learning techniques, Onprasonk et al. (2023) suggested that the crucial concern for estimating disease is that the clinical symptoms are similar to those of other diseases. Hence, the obtained regression coefficients might not precisely represent the actual relationship between environmental factors and disease. Machine learning, using open-source software packages like R Studio, drove this study. The order to identify a robust association and predict NCD patterns between environmental and economic factors across Thai provinces, the most accurate machine learning that investigates a number of classification algorithms is the Random Forest (RF) model. The RF model employs an ensemble technique that combines outcomes from numerous randomly generated decision trees. Each tree is built using a random subset of training data, ensuring diversity and guarding against overfitting.

Afterwards, Breiman (2001) aggregates the predictions from individual trees. Also, Hastie et al. (2009) [14] looked at variable minimal depth (MD) to find out how much each variable affected the accuracy of an RF model's predictions. Hence, equipped MD and RF provide a deeper understanding of the relationship between each variable and the predicted outcome.

B. Spatial analysis

This study used Geographic Information System (GIS) software to integrate various datasets in the spatial analysis method. Additionally, the Geoda program facilitated data representation in a map format, merging location data with descriptive information and also aiding in revealing patterns of geographic context to study spatial association. The study employed two spatial methods:

1) Moran's I Statistic: The spatial autocorrelation statistic was one of the univariate computational techniques for quantifying the degree of spatial autocorrelation. Moran's, I value ranges between −1 and 1. Where the value was close to 1, it indicated a highly positive spatial autocorrelation; otherwise, it indicated an extremely negative one. While Moran's I has a zero value, there is no spatial autocorrelation.

2) Local Indicators of Spatial Association (LISA): This method gauged data concentration at the spatial level and identified clustering patterns' locations. LISA generated outcomes, including a cluster map showcasing four categories of spatial correlations: high-high, low-low, low-high, and high-low (Anselin, 1995).

4. Result

The model identified a crucial node intersection at 4.16 using cross-validation and data resampling techniques. This selected node served as an optimal threshold, allowing us to effectively identify the influencing factors for each disease.

4.1 Influencing factor on NCDs

1. Diabetes disease

The diabetes cases, the model achieved a high accuracy of 99%, indicating its effectiveness in predicting mortality from diabetes based on the provided data, with an R-squared of 0.741, indicating that the model can explain 74.1% of the variation in mortality from diabetes.

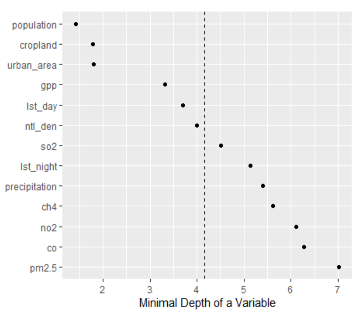


Figure 2: Minimal depth analysis of diabetes

The minimal depth analysis exposed the most important factors for mortality from diabetes included population density, urban area, GPP, cropland area, nighttime light density (NTL), and land surface temperature (daytime), as presented in Figure 2.

2. Hypertension disease

In the case of hypertension, the model achieved a high accuracy of 98.6%, indicating its effectiveness in predicting mortality based on the provided data, with an R-squared of 0.588, indicating that the model can explain 58.8% of the variation in mortality from hypertension.

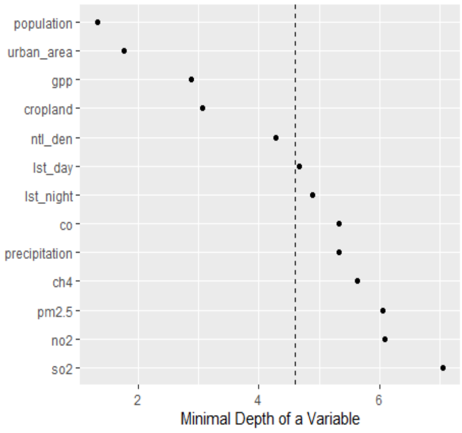


Figure 3: **Minimal depth analysis hypertension disease**

The minimal depth analysis revealed that the most influential factors for mortality from hypertension included population, urban area, GPP, cropland area, and nighttime light density (NTL), as shown in Figure 3.

3. Ischemic disease

In the case of ischemic, the model had a high accuracy rate of 99.6%, which means it was good at predicting death from ischemic disease based on the data given. It also had an R-squared of 0.754, which means it can explain 75.4% of the variation in death from ischemic.

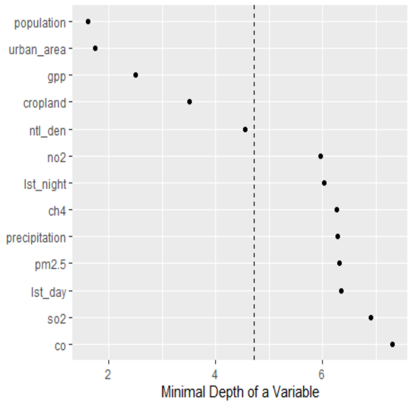


Figure 4: Minimal depth analysis of ischemic disease

The minimal depth analysis revealed that the most influential factors for mortality from ischemic included population, urban area, GPP, cropland area, and nighttime light density (NTL), as shown in Figure 4

4. Chronic disease

Chronic disease With an R-squared of 0.627, the model can explain 62.7% of the variation in mortality from chronic. The model demonstrated a high accuracy rate of 98.81% in predicting the prevalence of death from chronic conditions, based on the provided data.

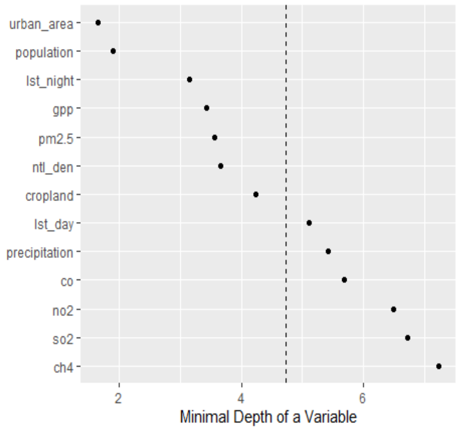


Figure 5 : Minimal depth analysis of chronic disease

Figure 5 shows that the minimal depth analysis showed that population, urban area, GPP, cropland area, nighttime light density (NTL), PM 2.5, and land surface temperature (nighttime) were the most important factors for chronic mortality.

4.2 Spatial Distribution of Disease

This part goes into more detail about the results of the random forest algorithm by looking at both one-way and two-way connections between differences in geography and NCD deaths at the provincial level. We employed the LISA method to verify the spatial relationship. This statistical analysis used a color scheme on the map to illustrate the correlation between influencing factors and NCD mortality. The color scheme categorized correlations into four groups: dark-red, light-red, dark-blue, and light-blue, representing different levels of spatial autocorrelation. However, the study primarily focused on the dark-red scheme, highlighting areas with severe mortality from NCDs that could potentially benefit from public health policy interventions.

1) Diabetes disease

The outcomes showed the localized correlation between satellite-based indicators: population, urban area, GPP, cropland area, NTL, and daytime. The northeast region, including Nong Bua Lamphu, Khon Kaen, Chaiyaphum, Maha Sarakham, Buri Ram, Surin, Si Sa Ket, Roi Et, Kalasin, and Mukdahan, had the highest incidence rate of diabetes mortality. Table 1 displays the results.

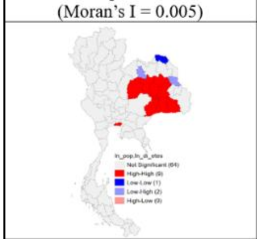
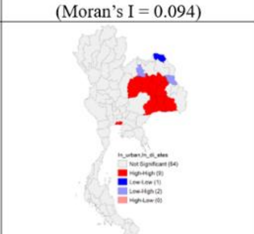
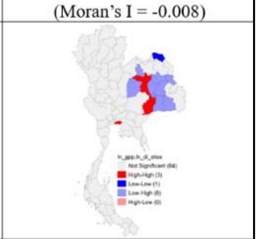
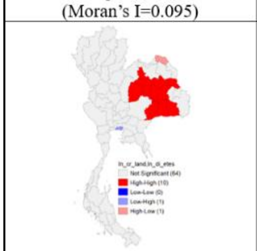
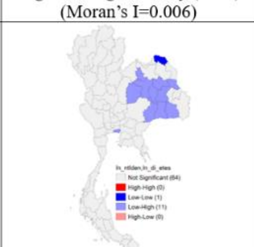
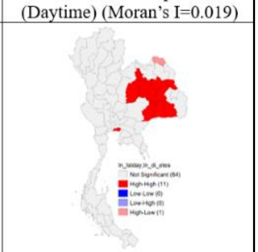
Population (Moran's I = 0.005)	Urban area (Moran's I = 0.094)	GPP (Moran's I = -0.008)
		
Cropland area (Moran's I=0.095)	Nighttime light density (NTL) (Moran's I=0.006)	Land surface temperature (Daytime) (Moran's I=0.019)
		

Table 1 displays LISA's cluster map, which shows the localized association between influencing factors and diabetes.

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2) Hypertension disease

The outcomes showed a localized correlation between satellite-based indicators such as population, urban area, GPP, cropland area, and NTL. Some province regions, including Chiang Rai, Lampang, Uttaradit, and Phichit, showed a high incidence rate of hypertension mortality. Sakon Nakhon, Udon Thani, and Surin were in the northeast, while Surat Thani and Phang Nga were in the southeast. Table 2 displays the results.

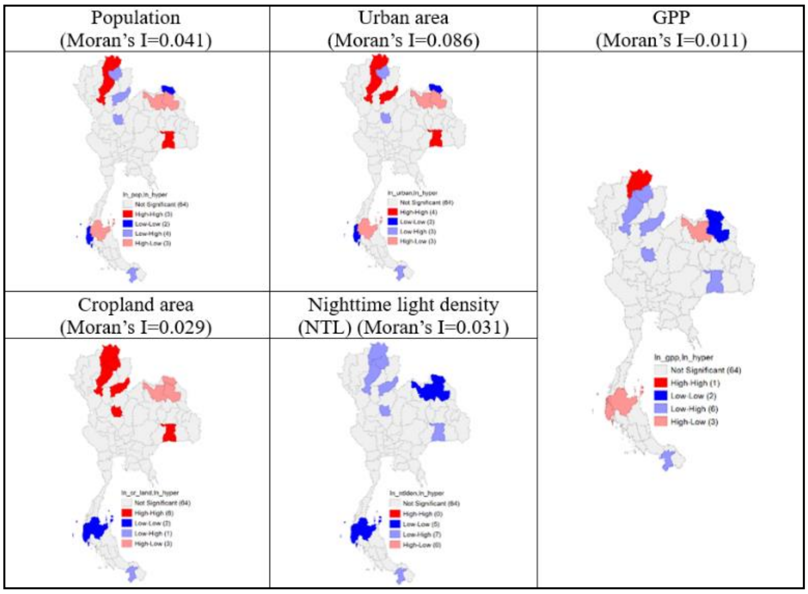


Table 2 shows LISA's cluster map, which demonstrates the localized association between influencing factors and hypertension.

3) Ischemic disease

The outcomes showed a localized correlation between satellite-based indicators such as population, urban area, GPP, cropland area, and NTL. The center region, including Bangkok, Nonthaburi, Pathum Thani, Phra Nakhon Si Ayutthaya, Samut Prakan, Samut Sakhon, Chachoengsao, Nakhon Pathom, and Saraburi, had the highest incidence rate of ischemic mortality. Table 3 exhibits the results in several provinces in the northeast region, including Sakon Nakhon, Nakhon Phanom, and Udon Thani.

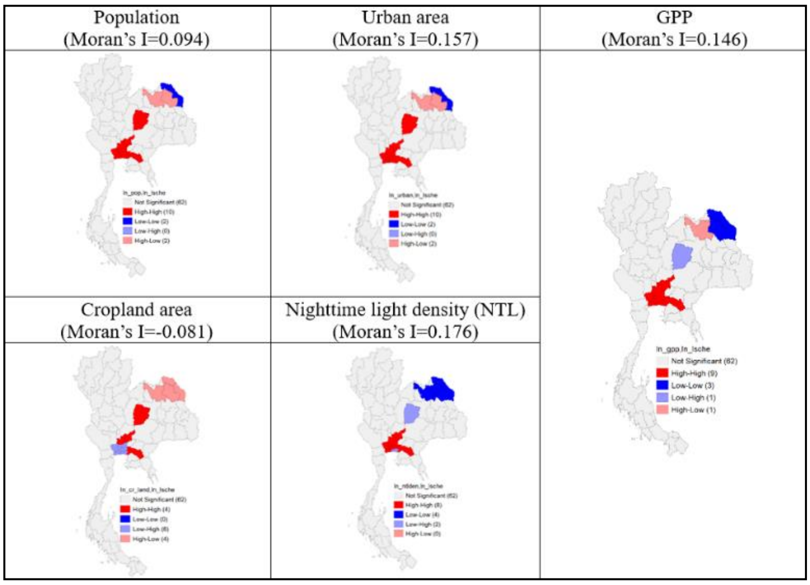


Table 3: LISA's cluster map showing the localized association between influencing factors and ischemic.

4) Chronic disease

The chronic mortality incidence rate was found in the mostly in northern region, including Mae Hong Son, Chiang Mai, Lamphun, Lampang, Uttaradit, Chiang Rai, Phayao, and some provinces from the center and northeast, such as Bangkok, Suphanburi, Ratchaburi Chaiyaphum, and Ubon Ratchathani, had the highest incidence rate of chronic mortality. The outcomes showed a localized correlation between satellite-based indicators: population, urban area, GPP, cropland area, NTL, PM 2.5, and nighttime. Table 4 exhibits the results.

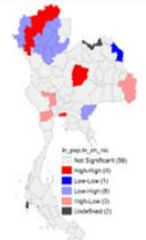
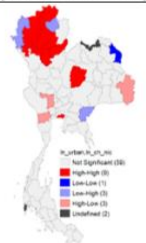
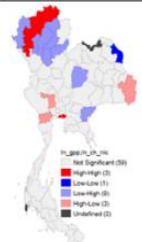
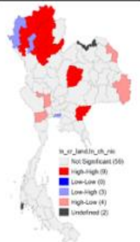
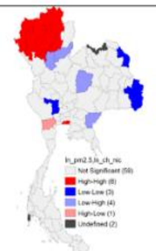
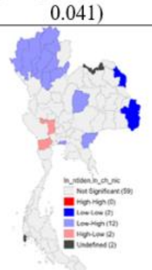
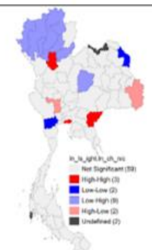
Population (Moran's I=0.017)	Urban area (Moran's I=0.118)	GPP (Moran's I=0.029)	Cropland area (Moran's I=0.011)
			
PM 2.5 (Moran's I=0.219)	Nighttime light density (NTL) (Moran's I=-0.041)	Land Surface Temperature (Nighttime) (Moran's I=-0.001)	
			

Table 4 shows LISA's cluster map, showing the localized association between influencing factors and chronic.

5. Result Analysis

Overall, the result reports that environmental and economic factors affected NCD mortality. The random forest minimal mortality was influenced by various factors such as population, urban area, GPP, cropland area, and nighttime light density (NTL). These factors varied depending on the specific type of NCD disease, such as diabetes, which is associated with a hot zone. Therefore, the factor was related to the island surface temperature during the day. Moreover, the chronic effects of pollution and urbanization make the PM and NTL significant. Similar to the main findings of Chakravorty and Heath [15] and Hantrakun et al. [16], the present work indicated that the provinces with hotspot clusters were primarily located in the northeast because their physical conditions and climate are agricultural land and drought. Environmental factors such as rainfall, vegetation, temperature, and climatic variations particularly influence the highest diabetes mortality incidence rate. Additionally, we employed spatial analysis to statistically quantify the extent of NCD mortality across Thailand. The results revealed variations in the NCD mortality rate across different regions of the country.

The northeastern region, including Nong Bua Lamphu, Khon Kaen, Chaiyaphum, Maha Sarakham, Buri Ram, Surin, Si Sa Ket, Roi Et, Kalasin, and Mukdahan, exhibited the highest concentration of diabetes mortality. The outcomes of bivariate LISA showed the localized correlation between satellite-based indicators: population, urban area, GPP, cropland area, nighttime light density (NTL), and land surface temperature (daytime). The results suggested that the cultivation area, as indicated by the cropland index, played a significant role in this trend. Diabetes prevalence is severe in rural areas, particularly in the northeast region, where farmers often face low incomes and food insecurity. Conversely, areas with lower concentrations of nighttime light or lower socioeconomic development were also likely to experience higher rates of diabetes. Savage et al. (2021) proposed the DR-NCD risk framework, highlighting how structural drivers like climate change can exacerbate dietary-related non-communicable diseases. In contrast, Bangkok, with its sprawling urban areas and influx of migrant workers, emerged as a hotspot for NCD mortality. This was consistent with findings by Moon (2021) [17], indicating that heat waves increase mortality and morbidity risks for diabetes patients. During such events, mortality rates among diabetes patients may rise by approximately 18 percent, with a corresponding 10 percent increase in overall morbidity.

The incidence rate of hypertension-related mortality was higher in certain provinces, such as Chiang Rai, Lampang, Uttaradit, and Phichit in the northern region, and Sakon Nakhon, Udon Thani, and Surin in the northeast. Furthermore, in the southeast region, Surat Thani and Phang Nga showed elevated rates. Bivariate LISA analysis revealed a localized correlation between satellite-based indicators, including population density, urban area, GPP, cropland area, and nighttime light density (NTL). Similarly, the incidence of ischemic mortality was highest in central regions such as Bangkok, Nonthaburi, Pathum Thani, Phra Nakhon Si Ayutthaya, Samut Prakan, Samut Sakhon, Chachoengsao, Nakhon Pathom, and Saraburi. Some provinces in the northeast, such as Sakon Nakhon and Nakhon Phanom, also exhibited high rates. The urban area index appeared to play a significant role, as rural areas showed lower prevalence, detection, and treatment rates of hypertension compared to urban areas. This aligns with findings by Ratovoson et al. (2015) [18], indicating that hypertension was more prevalent in rural areas yet significantly less treated. Consequently, there is a growing risk of a major epidemic of cardiovascular diseases in Madagascar's aging society.

The incidence rate of chronic-related mortality was highest in the northern region, including provinces like Mae Hong Son, Chiang Mai, Lamphun, Lampang, Uttaradit, Chiang Rai, and Phayao. Additionally, some provinces in the central and northeastern regions, such as Bangkok, Suphanburi, Ratchaburi, Chaiyaphum, and Ubon Ratchathani, also showed elevated rates. Satellite-based indicators like population density, urban area, GPP, cropland area, nighttime light density (NTL), PM 2.5, and land surface temperature (Nighttime) were found to be locally correlated. The presence of PM 2.5 suggests air pollution, particularly in the northern region, which often experiences pollution from forest fires.

6. Conclusion

The study identified high-risk clusters, as well as the spatial dynamics of NCD mortality and its determinants. These findings highlight the complex interplay between environmental, economic, and demographic factors that influence the prevalence of NCD mortality in Thailand. The results indicated significant implications for public health policy and intervention strategies aimed at addressing the risk factors associated with each disease. By understanding and targeting these factors, policymakers can develop more effective strategies to promote public health and well-being, ultimately reducing the burden of NCD in the country.

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