DIVERGENT NIGHTTIME LIGHT DYNAMICS IN BANGKOK AND SURROUNDING PROVINCES DURING THE COVID-19 PANDEMIC: INSIGHTS FROM GOOGLE EARTH ENGINE

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ABSTRACT

This study investigates the dynamics of nighttime light (NTL) intensity in the Bangkok Metropolitan Region (BMR), Thailand, during the COVID-19 pandemic using Google Earth Engine (GEE). Leveraging the cloud-based processing capabilities of GEE, we analyzed Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) data to assess the spatial and temporal impacts of the pandemic on human activity and socioeconomic conditions across different urban zones. The Average Light Index (*ALI*) and Index of Change (*ICH*) were calculated to quantify and compare changes in NTL intensity between Bangkok and its surrounding provinces. Results revealed a general decrease in NTL intensity during the initial year of the pandemic (2020), particularly in the central business districts of Bangkok, with a mean *ICH* value of 95.28 indicating a decrease of approximately 4.72%. However, the surrounding districts exhibited greater resilience, with a mean *ICH* value of 99.56 indicating a slight increase in NTL intensity. A partial recovery was observed in the post-pandemic period (2021), with Bangkok's mean *ICH* value rising to 99.38, but certain districts, especially those reliant on tourism or entertainment, continued to exhibit lower NTL intensity compared to pre-pandemic levels. This study underscores the diverse and spatially varied impacts of the COVID-19 pandemic on NTL dynamics across the BMR, highlighting the importance of considering the heterogeneous nature of urban areas when assessing pandemic-related effects and formulating recovery strategies.

Key-words: *Nighttime lights, COVID-19 impacts, Urban dynamics, Google Earth Engine.*

1. INTRODUCTION

The COVID-19 pandemic profoundly impacted public health, economies, and societies worldwide (World Bank, 2022). Governments implemented strict measures to curb the spread of the virus, including lockdowns, travel restrictions, and social distancing protocols. These measures led to significant disruptions in various sectors, with lasting consequences for urban areas (Naseer et al., 2023).

While the immediate health crisis has subsided, the long-term consequences of the pandemic continue to unfold, with significant implications for urban areas (Sharifi & Khavarian-Garmsir, 2020). A study by Wolff and Mykhnenko (2023) highlighted the uneven impact of the pandemic on cities, with some experiencing more severe economic and social disruption than others.

Thailand experienced its first wave of COVID-19 in early 2020, prompting a state of emergency and stringent measures to control the outbreak (DDC, 2024). Subsequent waves further exacerbated the situation, with cumulative cases exceeding one million by late 2021.

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While the situation has gradually improved through vaccination efforts and government interventions, Thailand continues to face challenges in its recovery (Ministry of Foreign Affairs of Thailand, 2020; Bank of Thailand, 2020).

In Europe, the pandemic has reshaped urban landscapes and accelerated existing trends such as the rise of remote work and the growth of online businesses. A study published in Cities (Wolff & Mykhnenko, 2023) found that the pandemic led to a significant decrease in commuting. Furthermore, there was an increase in residential mobility, with people relocating from city centers to suburban areas to escape overcrowding and reduce the risk of infection.

Identifying areas requiring targeted recovery and development efforts is crucial for the nation's progress (UNDRR, 2015; Deonarine et al., 2021). This study has important implications for understanding the social, economic, and environmental impacts of the COVID-19 pandemic on urban areas. To achieve this understanding, geospatial technologies offer powerful tools for analyzing the impacts of such events. Cloud-based platforms like GEE are particularly useful for this purpose. NTL data is readily available within GEE. It has proven valuable in assessing urban dynamics and spatial inequalities. This is particularly true in response to significant events (Li & Zhou, 2017; Gorelick et al., 2017; Ma, Huang & Liu. 2022; Itsarawisut, Puckdeevongs & Laosuwan, 2024). The European Space Agency (2024) has utilized GEE to monitor the impact of COVID-19 on air quality and urban green spaces across Europe. For example, Wang et al. (2024) used NTL data and GEE to analyze how COVID-19 impacted urban networks, demonstrating the value of these tools for understanding urban resilience and adaptation. This highlights the potential of NTL data and GEE to inform urban recovery and sustainable development.

This study investigates the impacts of the COVID-19 pandemic on human activities and urban dynamics in the BMR using NTL data and GEE. The analysis focuses on identifying the social, economic, and ecological implications of the pandemic and providing insights for urban recovery and sustainable development. For example, the analysis of NTL data can reveal how the pandemic has affected human activities and behaviors in different parts of the BMR, such as changes in commuting patterns, leisure activities, and social gatherings. This information can be used to understand the social consequences of the pandemic and to develop policies to mitigate its negative impacts. Furthermore, the findings can inform recovery efforts by identifying areas that experienced the most significant declines in NTL intensity, which may indicate areas with the greatest economic distress and require targeted support for businesses and employment. From an ecological perspective, the use of GEE for NTL analysis promotes sustainable practices by reducing the need for energy-intensive on-site data collection and processing, contributing to a lower carbon footprint for research activities.

NTL data has become a valuable tool for monitoring human activity. This data is observed by satellites such as the VIIRS DNB. It can be used to monitor economic activity, urban development, and environmental changes (Min et al., 2015; Bagayoko, Kadengye & Runyenje, 2018). Recent studies have utilized VIIRS DNB data to investigate the impact of the COVID-19 pandemic on human activity by examining changes in NTL intensity. For example, Pavlačka et al. (2023) investigated the impact of COVID-19 on NTL intensity in the Czech Republic using VIIRS DNB data. They found that light intensity decreased during lockdown periods, consistent with other studies conducted in various countries such as India, France, Vietnam and the United States (Deepab & Gupta, 2021; Xu et al., 2021; Kovács, 2022).

This study builds upon our previous exploratory work applying GEE to analyze NTL dynamics in Bangkok during the COVID-19 pandemic. This unpublished work investigated the impacts of COVID-19 on NTL within Bangkok, revealing spatial and temporal variations in changes in human activities. While that work focused solely on the urban core, this study expands the scope to encompass the broader BMR, including both the densely urbanized core and the surrounding peri-urban areas, as illustrated in **Fig. 1**. This broader perspective allows for an investigation into the potentially divergent impacts of the pandemic across varying levels of urbanization, which can further support the development of more location-specific recovery policies tailored to the unique characteristics of each area.

By leveraging the capabilities of GEE, this study analyzes NTL satellite imagery to assess NTL changes in the BMR across the pre-pandemic, pandemic, and post-pandemic periods. The analysis aims to reveal spatial patterns and variations in pandemic-related impacts on human activity and mobility across different zones of the BMR.

While changes in NTL intensity can provide preliminary insights into potential impacts (Andries et al., 2023), this study serves as an initial screening. Further investigation and ground-truthing are necessary to definitively link observed changes to the pandemic and to determine the specific nature and extent of the impacts (Liu et al., 2024). Nevertheless, the spatial patterns identified through NTL analysis can guide further research and targeted interventions for recovery and development (Mitsova et al., 2024).

The findings of this study will provide valuable information for agencies and organizations involved in recovery planning and economic and social development (Wang et al., 2024).

2. STUDY AREA

This study focuses on the BMR in Thailand, which includes 50 districts in Bangkok and 29 districts in the surrounding five provinces: Nonthaburi, Pathum Thani, Samut Prakan, Nakhon Pathom, and Samut Sakhon. The BMR is Thailand's economic, transportation, and social hub (Peungnumsai et al., 2020), with a population of approximately 10 million people residing in its 7,701.56 sq.km area (LDD, 2019), making it the most populous region in Thailand. The COVID-19 pandemic and related lockdown measures had a substantial impact on daily life and the economy here. The restrictions, such as lockdowns and travel limitations, led to noticeable changes in activity levels across both central and outer areas (Sirikeratikul & Nicely, 2020).

The population density in Bangkok averages 3,503 persons/sq.km, while the surrounding five provinces have an average population density of 861 persons/sq.km (BMA, 2023; DPT, 2023). This difference in population density reflects the varying levels of urbanization and economic activity across the BMR. Approximately 67% of Bangkok's total area consists of urban areas and built-up environments, compared to only 30% in the surrounding five provinces (LDD, 2019), highlighting the significant difference in urban development and land use patterns between Bangkok and its neighboring provinces (**Fig. 1**).

The mix of urban and peri-urban environments within the BMR provides a unique opportunity to analyze the diverse impacts of the COVID-19 pandemic on NTL dynamics across different land use types and socioeconomic conditions. The BMR's geographical and social characteristics vary significantly. Bangkok itself is densely populated with high economic activity, while the surrounding provinces consist of residential neighborhoods and industrial zones (Peungnumsai et al., 2020). This division allows for a closer examination of changes in NTL intensity across different types of districts, shedding light on how the pandemic impacted urban and suburban life in unique ways.

3. DATA AND METHODS

3.1. Data Acquisition and Preprocessing

This study utilizes two primary data sources. The first is a vector layer delineating the administrative boundaries of the BMR. This layer encompasses 79 districts, comprising 50 districts within Bangkok and 29 districts across the five adjacent provinces: Nonthaburi, Pathum Thani, Samut Prakan, Nakhon Pathom, and Samut Sakhon. This vector layer serves as the spatial framework for the analysis.

The second data source is NTL data obtained from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) Composites Version 1 dataset, produced by the Earth Observation Group, Payne Institute for Public Policy, Colorado School of Mines (Earth Observation Group, 2020). This dataset, accessible through GEE, provides monthly cloud-free average radiance composites, capturing light emissions in the 400-900 nm wavelength range. The VIIRS DNB sensor onboard the Suomi National Polar-orbiting Partnership (NPP) satellite measures NTL with a spatial resolution of approximately 460 meters. The DNB data records radiance values in nanowatts per steradian per square centimeter, encompassing light emitted from various sources such as streetlights, buildings, and vehicles (Elvidge et al., 2009).

For this analysis, imagery from April of each year (2019, 2020, and 2021) was selected to represent the pre-pandemic, pandemic, and post-pandemic conditions, respectively. This selection allows for a consistent temporal comparison of NTL patterns across the study period.

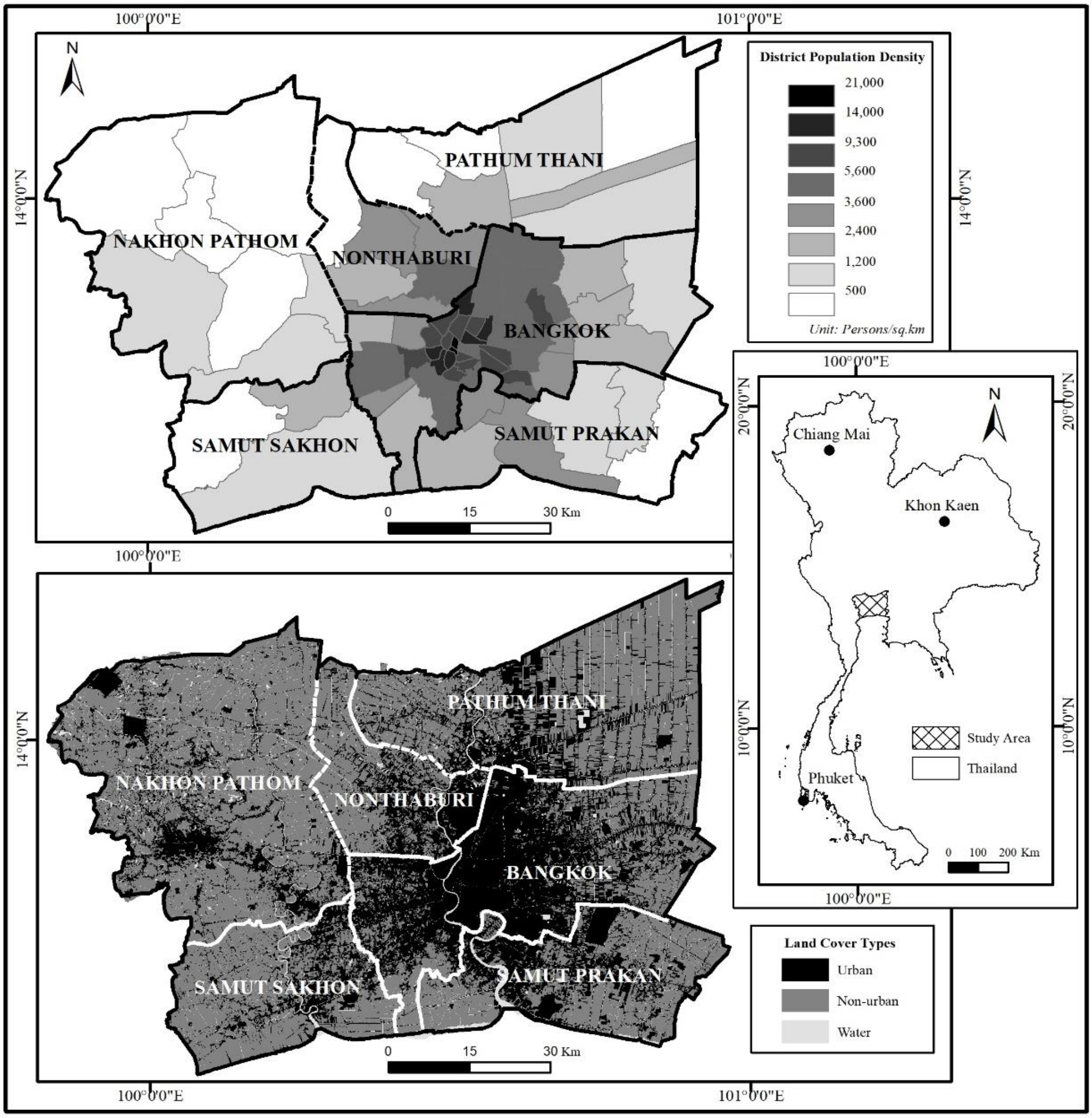

Fig. 1. Study area, population density, and urban extent. Source: Population density data from BMA (2023) and DPT (2023); Urban extent data from LDD (2019).

3.2. Data Processing and Analysis within GEE

All data processing and analysis were performed within the GEE cloud computing platform, which enables efficient handling and analysis of large geospatial datasets (Sunarta & Saifulloh, 2022). The Google Earth Engine-based analysis was implemented via a GEE coding script (https://code.earthengine.google.com/5b84ba93ea269e258805992d64660dc0).

The entire process, detailed in the following sections, consists of 3 main steps: 1) mean-based imputation for continuity., 2) calculation of the Average Light Index (*ALI*)., and 3) calculation of the Index of Change (*ICH*).

Mean-based imputation for continuity: Although the VIIRS DNB dataset provides monthly cloud-free composites, some pixels may still contain null values due to persistent cloud cover or other data acquisition issues. To address this, the focal mean () function in GEE was employed to fill null pixels with the average value of surrounding pixels within a 2.5-pixel radius, using a square kernel. This spatial interpolation technique ensured data continuity and minimized the influence of missing values on subsequent analyses.

Calculation of the *ALI*: To facilitate district-level analysis, the *ALI* was computed for each of the 79 districts within the BMR. This involved utilizing GEE's zonal statistics capabilities to calculate the sum of the products of each pixel's DNB value and its area within each district polygon, subsequently dividing by the total district area to obtain the *ALI*. This index represents the average NTL intensity within each district. The mathematical expression for *ALI* calculation (Pavlačka et al., 2023) is as follows.

$$ALI_i = \frac{\sum DNB_p A_p}{A_i} \tag{1}$$

where ALI_i is the Average Light Index of i-th district, p is the number of patches (a patch is a grid cell or a part of a grid cell intersected by the district border), DNB_p is the digital number (radiance value) of the p-th patch, A_p is the area of the p-th patch, and A_i is the area of the i-th district.

Calculation of the *ICH*: To quantify the relative changes in NTL intensity between the pre-pandemic year (2019) and the pandemic/post-pandemic years (2020 and 2021), the *ICH* was calculated. This involved comparing the *ALI* of each district in 2020 and 2021 to its *ALI* in 2019. The formula for *ICH* (Pavlačka et al., 2023) is:

$$ICH_{yi} = \frac{100 ALI_{yi}}{ALI_{2019i}} \tag{2}$$

where ICH_{yi} represents the Index of Change for a specific District (i) in a given year (y, either 2020 or 2021), ALI_{2019i} denotes the ALI for the same District (i) in 2019.

The resulting ICH_{yi} value indicates the percentage change in *ALI* for that District between the specified year and 2019. An ICH_{yi} of 100 signifies no change, a value greater than 100 represents an increase (indicated by a '+' symbol), and a value less than 100 indicates a decrease (indicated by a '-' symbol) in *ALI* compared to 2019.

3.3. Separate Calculations for Bangkok and Surrounding Provinces

To assess the differential impacts of the COVID-19 pandemic on NTL dynamics in Bangkok and the surrounding provinces, the *ALI* and *ICH* calculations were performed separately for the two areas. This involved subsetting the BMR vector layer into two distinct layers: one representing the 50 districts of Bangkok and the other representing the 29 districts of the surrounding provinces. The zonal statistics and *ICH* calculations were then applied to each subset independently, allowing for a direct comparison of NTL changes between the urban core and the peri-urban areas.

3.4. Statistical evaluation and Visualization

To assess the inter-annual variations in NTL intensity, a comparative analysis of DNB values and the derived *ALI* was conducted for each year. This analysis employed basic statistical indicators, including minimum, maximum, median, mean, and standard deviation. These indicators were calculated separately for Bangkok and the surrounding provinces to characterize the distribution of NTL intensity and its changes over time.

Furthermore, these statistical indicators were utilized to characterize the distribution of the *ICH*, with 2019 serving as the baseline year. Histograms were generated to visualize the density distribution of *ICH* values across all districts within the defined study area, providing insights into the overall patterns of change in NTL intensity.

3.5. Typology of Change Trends

A typology was developed to categorize the year-on-year changes in *ALI* into four logical categories based on increases or decreases relative to 2019 (**Table 1**). This typology facilitates a more nuanced understanding of the temporal dynamics of NTL changes in response to the pandemic.

Table 1.
Typology of trend of change.

Type	2019-2020	2019-2021
+ +	Increase,	Increase.
- +	Decrease,	Increase.
- -	Decrease,	Decrease.
+ -	Increase,	Decrease.

4. RESULTS

4.1. Descriptive Statistics

Basic statistical measures (minimum, maximum, median, mean, and standard deviation) were computed for both the raw VIIRS DNB values and the derived *ALI* for each year (2019, 2020, and 2021). These statistics, generated within the GEE environment, provide a preliminary overview of the central tendency and variability of NTL intensity across districts within both Bangkok and the surrounding provinces. Specifically, the nighttime light data used in this analysis consisted of gridded layers of DNB, generated for April of 2019, 2020, and 2021, as visualized in **Fig. 2**.

As shown in **Table 2**, the distribution of DNB values in Bangkok during the pre-pandemic year (2019) exhibited the highest variability compared to 2020 and 2021, as evidenced by the highest standard deviation (SD = 18.00). While the mean DNB value was relatively high in 2019, the median DNB value was slightly lower in 2019 compared to 2021. In contrast, the surrounding provinces showed a different trend, with the highest mean DNB value observed in 2021, although the variability remained relatively consistent across the three years.

For the *ALI* values in Bangkok, both the mean and median were highest in the pre-pandemic year (2019), with a noticeable decrease observed in 2020, followed by a partial recovery in 2021. This pattern suggests a reduction in NTL intensity in Bangkok during the COVID-19 pandemic, with a subsequent rebound in activity in the post-pandemic period. However, the surrounding provinces did not exhibit the same trend. While the mean *ALI* value slightly decreased in 2020, it increased in 2021, exceeding the pre-pandemic level. This observation suggests distinct changes in NTL activity between the urban core (Bangkok) to the peri-urban areas (surrounding provinces) during the pandemic.

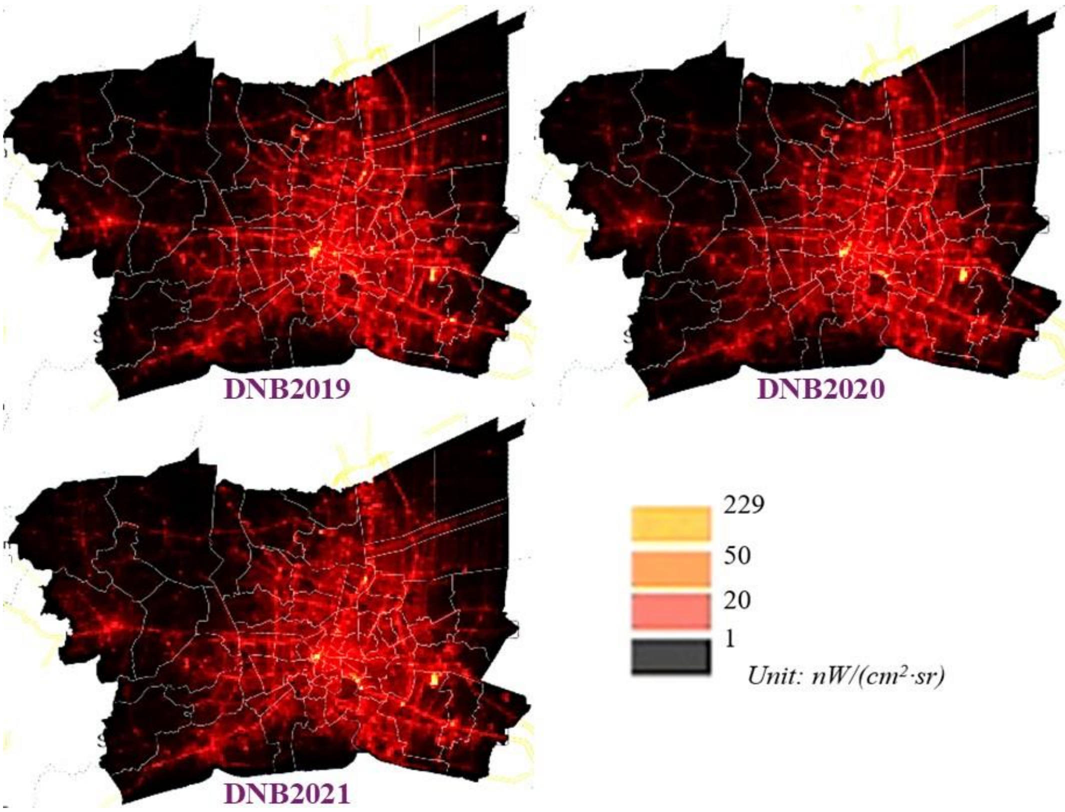

Fig. 2. NTL intensity (DNB) in the BMR during April 2019, 2020, and 2021. Source: Authors' elaboration.

4.2. Index of Change (*ICH*) Analysis

The *ICH*, calculated using GEE for 2020 and 2021 relative to the 2019 baseline, revealed the percentage change in *ALI* for each district. Histograms (**Fig. 3**) were generated within GEE to visualize the distribution of *ICH* values across the districts in both Bangkok and the surrounding provinces, providing insights into the spatial patterns of change in NTL intensity.

Table 2.
Statistical characteristics of original DNB and *ALI* values in Bangkok and the surrounding provinces during April 2019, 2020, and 2021.

Region	Dataset	Min	Median	Mean	Max	SD
Bangkok	DNB2019	1.13	20.52	23.24	229.08	18.00
	DNB2020	1.16	20.47	22.43	218.44	16.56
	DNB2021	0.83	21.02	23.41	215.11	17.44
	ALI2019	4.76	24.12	26.00	77.95	11.76
	ALI2020	4.55	22.81	24.38	70.06	10.18
	ALI2021	4.75	23.04	25.30	69.96	10.35
Surrounding Provinces	DNB2019	0.68	4.70	9.02	186.25	10.72
	DNB2020	0.81	4.76	8.90	159.29	10.24
	DNB2021	0.77	5.41	9.66	208.64	11.02
	ALI2019	1.77	8.31	9.95	23.12	6.38
	ALI2020	1.82	7.97	9.85	24.02	6.36
	ALI2021	1.94	8.96	10.54	23.43	6.47

In the surrounding provinces, the *ICH* distributions for both 2019-2020 and 2019-2021 are less skewed, with mean values of 99.56 and 108.62, respectively. Notably, the mean *ICH* value for 2019-2021 in the surrounding provinces exceeds 100, indicating an overall increase in NTL intensity compared to the 2019 baseline.

The lower mean *ICH* value in Bangkok in 2019-2020 compared to 2019-2021 underscores an overall reduction in NTL intensity during the initial year of the COVID-19 pandemic (2020), followed by a partial recovery in 2021. However, the surrounding provinces show a different trend, with a slight increase in mean *ICH* in 2020 and a more pronounced increase in 2021. This difference highlights the varying impacts of the pandemic and subsequent recovery on NTL dynamics in the urban core versus the peri-urban areas.

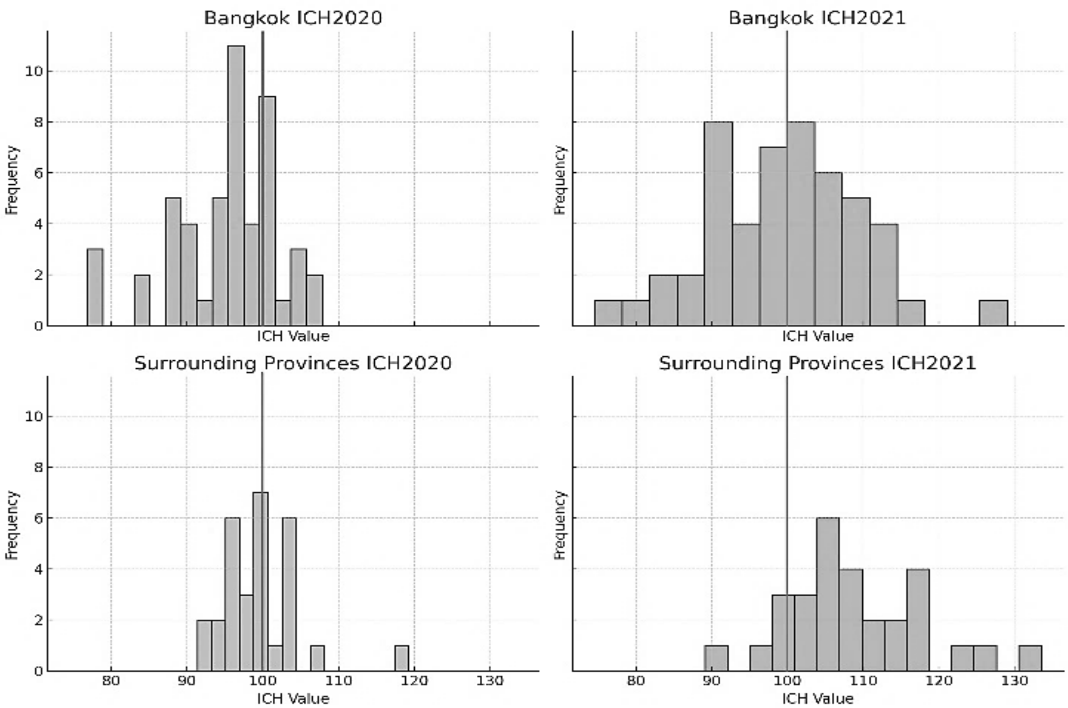

Fig. 3. Information model of the interaction of subsystem of city economy with the environment.
Source: Authors' elaboration.

Table 3.

Statistical characteristics of calculated *ICH* with the base year 2019.

Region	Dataset	Min	Median	Mean	Max	SD
Bangkok	ICH 2020	76.82	95.83	95.28	107.84	7.13
	ICH 2021	74.55	100.05	99.38	128.99	10.36
Surrounding Provinces	ICH 2020	91.33	98.99	99.56	119.30	5.37
	ICH 2021	89.11	107.29	108.62	133.48	9.24

4.3. Temporal and Spatial Trends

Further analysis of the *ICH* values and their spatial distribution, facilitated by GEE's visualization and mapping tools, highlights areas that experienced significant increases or decreases in NTL during the pandemic and post-pandemic periods. These trends will be discussed in relation to the known impacts of COVID-19 on the various districts within Bangkok and the surrounding provinces.

Fig.4 illustrate the spatial distribution of the *ICH*. This shows the change in NTL intensity across the districts. The *ICH* values for 2020 and 2021 are compared to the baseline year of 2019. An overall comparison between 2020 and 2021 reveals a greater decrease in light intensity in 2020. This is particularly true in certain districts within Bangkok.

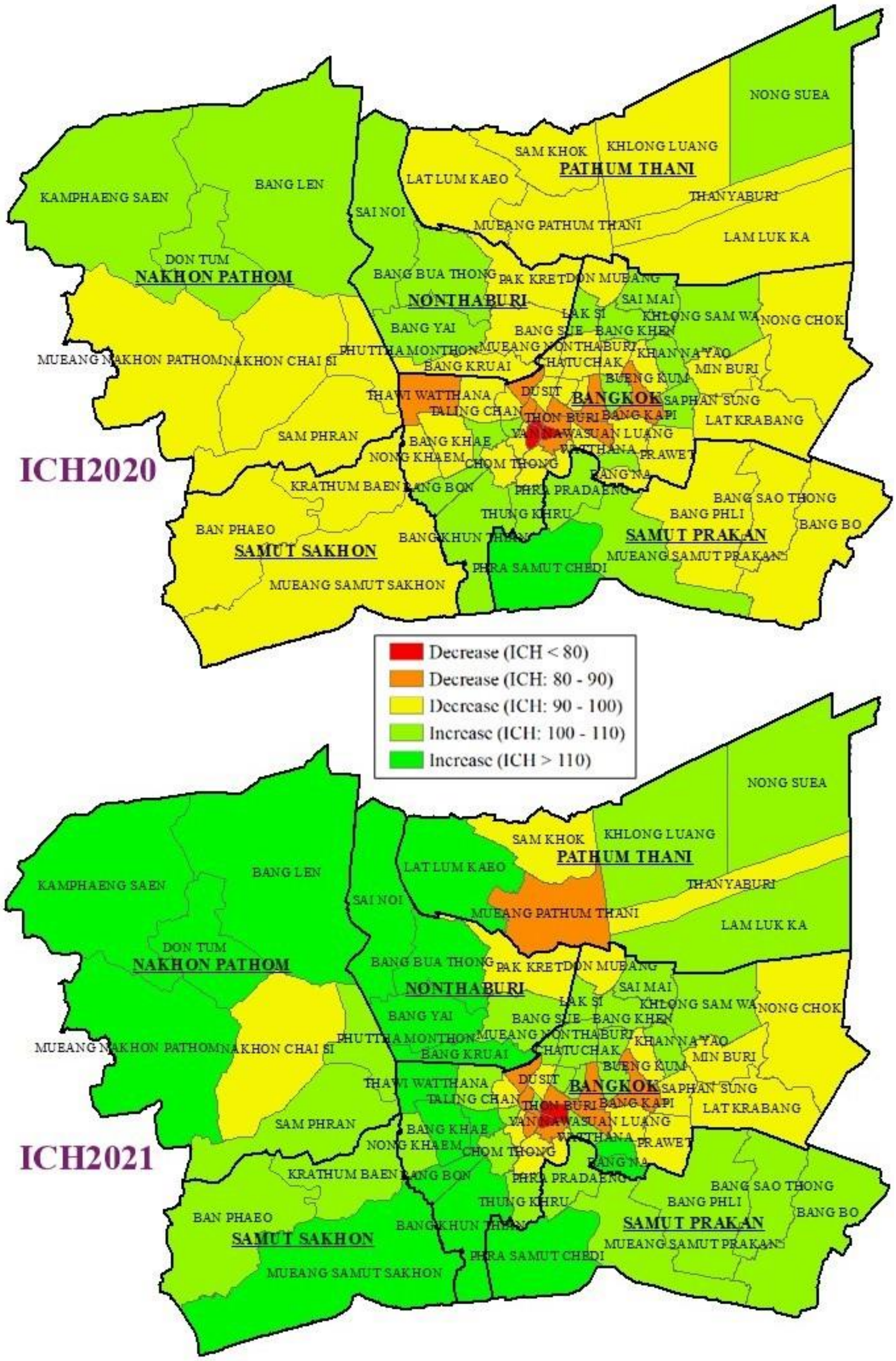

Fig. 4. Spatial Distribution of NTL Change in the Study Area, Classified by *ICH*.
Source: Authors' elaboration.

In 2020, during the peak of the pandemic and associated lockdowns, a majority of districts in Bangkok exhibited a decrease in NTL intensity, evident from their *ICH* values below 100. The most pronounced declines were concentrated in the central business districts (e.g., Pathum Wan, Sathon, Ratchathewi, and Watthana) and areas with high economic activity, reflecting the impact of restrictions on businesses and social gatherings. However, some districts in the outskirts of Bangkok, such as Bang Khen, Phra Khanong, Bang Kapi, and Bangkok Yai, showed an increase in NTL intensity during this period.

In 2021, following the easing of restrictions, a partial recovery in NTL intensity was observed in many districts in Bangkok, with fewer districts displaying *ICH* values below 100. Notably, districts with a strong industrial presence, such as Bang Khun Thian, Phasi Charoen, and Khlong Sam Wa, demonstrated a more pronounced rebound. However, some areas, especially those reliant on tourism or entertainment, such as Phra Nakhon and Khlong San, continued to exhibit lower NTL intensity compared to the pre-pandemic levels.

In the surrounding provinces, the spatial patterns of NTL change were more varied. While some districts experienced consistent decreases throughout the study period (e.g., Mueang Pathum Thani and Nakhon Chai Si), others showed increases in both years (e.g., Kamphaeng Saen and Don Tum). Many districts exhibited a decrease in 2020 followed by an increase in 2021, particularly those in close proximity to Bangkok.

4.4. Categorization of Change

The typology developed based on year-on-year changes in *ALI* will be presented in **Fig. 5**, showcases the four logical categories and their distribution across the BMR. This categorization, derived from the GEE analysis, aid in identifying districts that exhibited similar patterns of change in NTL intensity.

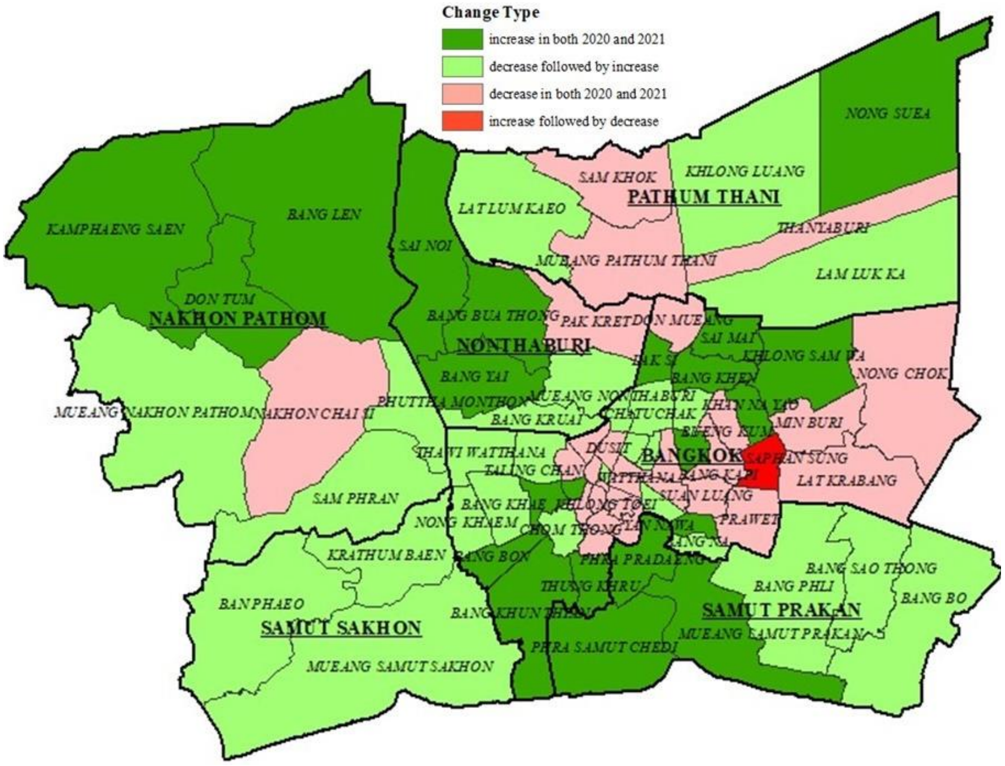

Fig. 5. Categorization of NTL Dynamics in the BMR During the COVID-19 Era.
Source: Authors' elaboration.

Table 4.

Frequencies and total area of the resulting types.

Region	Pattern Type	Frequency	Total area (km^2)	Share of area (%)
Bangkok	+ +	12	495.02	31.27
	- +	13	536.15	33.86
	- -	24	524.02	33.10
	+ -	1	28.07	1.77
	Sum		1,583.26	100.00
Surrounding Provinces	+ +	10	2,316.94	37.87
	- +	14	3,066.00	50.11
	- -	5	735.36	12.02
	+ -	0	0.00	0.00
	Sum		6,118.30	100.00

Fig. 5 and **Table 4** illustrate the distribution of NTL change patterns across the BMR between 2019 and 2021. These patterns reveal how light intensity changed in each district during the pandemic and post-pandemic periods. In Bangkok, the most common pattern was a continuous decrease in light intensity throughout 2020 and 2021 (- -). This pattern was observed in 24 districts, mainly in the city center. Thirteen districts, mostly in the outskirts or with industrial activity, experienced an initial decrease in 2020 followed by an increase in 2021 (- +). Twelve districts, also mainly on the outskirts, showed a continuous increase (+ +). Only one district, Saphan Sung, had an increase followed by a decrease (+ -).

In the surrounding provinces, the most common pattern was an initial decrease during the pandemic year (2020) followed by a subsequent increase in the post-pandemic year (2021) (- +), observed in 14 districts. This pattern was particularly prevalent in districts bordering Bangkok. The next most frequent patterns were a continuous increase in light intensity throughout both 2020 and 2021 (+ +), found in 10 districts, and a consistent decrease in light intensity throughout both years (- -), observed in 5 districts. No districts in the surrounding provinces exhibited an increase followed by a decrease (+ -).

The COVID-19 pandemic had diverse impacts on NTL dynamics across the BMR. These impacts varied spatially. Distinct patterns were observed in the urban core and peri-urban areas.

5. DISCUSSION

This study reveals substantial spatial and temporal variations in NTL intensity across the BMR during the COVID-19 pandemic. The observed decrease in NTL intensity during lockdowns aligns with previous studies documenting similar reductions in various urban areas worldwide (Liu et al., 2024). Kovács (2022) also reported comparable declines in NTL intensity during lockdowns, highlighting NTL data's utility in monitoring changes in human activities and urban dynamics in response to major disruptions like the pandemic. Furthermore, this supports Pesaresi et al. (2021), who emphasized the role of human activity changes, as seen in NTL patterns, on COVID-19 spread and socioeconomic impacts. The observed reductions can likely be attributed to restrictions on business, social gatherings, and mobility, leading to decreased economic activity and energy consumption.

Similar to our findings, Pavlačka et al. (2023) investigated the impact of COVID-19 on night-time lights in Czechia using VIIRS DNB data and found that the *ALI* exhibited a decrease of 18% in 2020 during the first big peak of the coronavirus pandemic. This decrease in NTL intensity was attributed to the substantial impact of restrictions on social and economic life during the pandemic. However, our study revealed a more pronounced decrease in NTL intensity during the first lockdown in April 2020. This difference may be attributed to the stricter lockdown measures implemented in

Thailand during April 2020, which included a nationwide curfew and the closure of most businesses and public spaces. Additionally, the first wave of the pandemic in Thailand coincided with the school break in April, which may have further contributed to the decrease in NTL intensity.

The spatial heterogeneity of the impacts, with certain districts experiencing more pronounced declines than others, also echoes observations from previous research, highlighting the uneven distribution of the pandemic's effects across urban areas (Sharifi & Khavarian-Garmsir, 2020; Da Schio et al., 2021; Liu et al., 2024). The central business districts and areas with high economic activity within Bangkok were the most affected, as these areas are highly dependent on the smooth flow of people and commercial activities. In contrast, residential areas and those in the surrounding provinces of the BMR showed greater resilience or even an increase in NTL, likely reflecting shifts in work and living patterns. The rise of remote work and the relocation of some businesses and residents to the outskirts of Bangkok may have contributed to this trend.

In contrast to Pavlačka et al. (2023), who analyzed NTL data for the entire month of October to avoid seasonal effects, our study focused on a single month (April) to represent pre-pandemic, pandemic, and post-pandemic conditions. This difference in temporal analysis approaches may account for some of the observed variations in the magnitude and patterns of NTL changes between the two studies.

A partial recovery was observed in the post-pandemic period, but certain districts within Bangkok, particularly those reliant on tourism or entertainment, continued to exhibit lower NTL intensity. This suggests that the economic recovery from the pandemic has been uneven, with some sectors taking longer to recover than others. The tourism and entertainment industries, which were severely impacted by travel restrictions and social distancing measures, are still struggling to regain their pre-pandemic levels of activity.

Notably, our study also highlights the distinct differences in NTL dynamics between 2020 and 2021. In 2020, the first wave of the pandemic led to a significant decline in NTL intensity, reflecting the widespread disruption to economic and social activities. However, in 2021, despite the ongoing pandemic and the emergence of new variants, NTL intensity showed signs of recovery, albeit with spatial variations across different districts. This suggests that there was a degree of adaptation and resilience to the pandemic's impacts in 2021, as people and businesses adjusted to the new normal and economic activities gradually resumed.

6. CONCLUSIONS

This study highlights the potential of GEE for analyzing NTL intensity in urban areas during crises. The COVID-19 pandemic is one example. The cloud-based processing capabilities of GEE enable rapid analysis of geospatial datasets. This provides valuable insights into spatial and temporal variations in human activity (Gorelick et al., 2017; Sunarta & Saifulloh, 2022; Tahiri et al., 2024).

This study highlights the heterogeneous impacts of the pandemic. These impacts vary across the BMR. Distinct patterns are observed in the urban core and peri-urban areas. This shows the importance of considering diverse urban areas when assessing pandemic effects and formulating recovery strategies. For instance, policymakers and urban planners can use NTL data to identify areas that experienced significant declines in nighttime light intensity during the pandemic, which may indicate areas requiring targeted recovery efforts. This could involve supporting businesses, creating jobs, and investing in infrastructure to revitalize these areas.

The findings have implications for post-pandemic urban recovery. The diverse impacts across the BMR underscore the need for tailored strategies for each area. For instance, the tourism and entertainment industries in the urban core may require specific support, while peri-urban areas may present different opportunities. NTL data can monitor crisis impacts and inform urban planning and disaster management. Integrating NTL data with socioeconomic and demographic datasets can enhance the understanding of the pandemic's multifaceted impacts.

While NTL data provides valuable insights into the spatial and temporal impacts of crises, it is important to recognize its inherent limitations. For instance, NTL data is prone to noise, especially in areas with low light intensity, and may lack sufficient resolution to accurately represent rural activities or small-scale economic changes. Additionally, the data may not fully capture human activities unrelated to artificial lighting, such as daytime economic or social activities. These limitations highlight the importance of validating findings through complementary data sources and ground-truthing efforts.

Ground-truthing is essential for linking observed changes in NTL intensity to specific socioeconomic or demographic contexts. For example, conducting field surveys or integrating NTL data with regional economic indicators can help validate the observed patterns and provide deeper insights into the underlying mechanisms. As emphasized by Deepab and Gupta (2021) and Liu et al. (2024), incorporating socioeconomic datasets with NTL analysis could improve the interpretation of changes and uncover local factors driving these variations.

Future research should explore the integration of NTL data with high-resolution satellite imagery and other emerging data sources, such as IoT sensors, to overcome these limitations. Advancing analytical techniques, such as machine learning, could further enhance the reliability and applicability of NTL-based findings in urban studies.

Nonetheless, this research contributes to the growing body of literature on the use of NTL data for monitoring and assessing the effects of crises and disasters. The application of GEE for efficient and scalable NTL analysis, as demonstrated in this study, opens up new possibilities for researchers and policymakers to leverage this valuable data source for evidence-based decision-making in urban planning, disaster management, and public health.

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