Original article

Outbreak, Surveillance, Investigation & Response (OSIR) Journal
ISSN 2651-1061 (Online)
https://he02.tci-thaijo.org/index.php/OSIR
Email: osireditor@osirjournal.net

March 2026
Volume 19, Issue 1
Article no. 278867

Role of Nighttime Lights on Cardiovascular Risk in Thailand: A Preliminary Ecological Analysis, 2024

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Received: 14 Nov 2025; Revised: 13 Feb 2026; Accepted: 20 Feb 2026
https://doi.org/10.59096/osir.v19i1.278867

Abstract

Objectives: Nighttime light (NTL) may serve as a proxy for urbanicity and circadian disruption, both of which are relevant to cardiovascular disease (CVD). This study aimed to examine the association between province-level NTL intensity and province-level CVD admission rates.

Methods: We conducted a nationwide ecological study of Thai provinces, linking satellite-derived NTL with 2024 inpatient CVD admissions for adults aged ≥40 years using a nationwide database from the Ministry of Public Health. Admissions for heart failure, acute myocardial infarction (MI), stroke, and atrial fibrillation (AF) were aggregated annually by province. The exposure was the intensity-based location quotient of smoothed nighttime light (LQSNL), using data from the Defense Meteorological Satellite Program—Operational Linescan System for 2010 and, in sensitivity analyses, data from the Suomi National Polar-orbiting Partnership/Visible Infrared Imaging Radiometer Suite for 2023. Associations were assessed with Pearson correlation and linear regression adjusted for the hospital bed capacity.

Results: Provinces with the highest LQSNL quartile had the highest CVD admission rates. LQSNL in 2010 correlated with MI (*r* 0.31, *p* <0.001), stroke (*r* 0.24, *p* 0.035), and AF (*r* 0.47, *p* <0.001) admissions. Using the 2023 LQSNL data yielded similar patterns. In multivariable models, higher LQSNL remained significantly associated with higher admission rates for all CVD outcomes across both exposure years.

Public Health Recommendations: These findings support the use of satellite-derived NTL as a practical proxy for spatial variation in estimating the CVD admission burden, with potential applications in surveillance and resource planning. Given the ecological design and potential for residual confounding, future studies should incorporate individual-level exposure and additional covariates, including demographic, environmental, and health system variables.

Keywords: ecological study, nighttime light, cardiovascular disease, incidence, Thailand

Introduction

Cardiovascular disease (CVD) remains the leading global cause of mortality, accounting for 20.5 million deaths in 2021, approximately one-third of all deaths, with more than half occurring in Asia.[1] The median age of patients with heart failure (HF) in the Asia-Pacific region is 67–70 years compared to 70–75 years for those in North America and Europe. Coupled with the more rapid rise in the incidence of atrial fibrillation (AF) in Asia, this pattern indicates a potentially greater future burden of AF–related heart failure in the region.[2–4] In Thailand, convergent evidence indicates increasing trends of CVD hospitalizations and projected risk, particularly among adults aged above 40 years old.[5–8]

Circadian rhythms support cardiovascular homeostasis by regulating blood pressure, glucose levels, hormone secretion, heart rate, conduction, and endothelial function.[9] Inappropriate rhythms elevate the CVD risk—acutely increasing hypercoagulability, heart rate, blood pressure, and inflammation while reducing vagal tone, and chronically driving fibrosis, hypertrophy, and remodeling that can culminate in HF.[9,10] Moreover, poor sleep health further fuels inflammation and cellular injury, worsening cardiovascular health, which in turn aggravates sleep problems—a self-reinforcing cycle.[11]

It is believed that nighttime light (NTL) exposure disrupts circadian rhythms, leading to poor sleep health, and potentially increasing the risk of developing CVD.[12,13] Previous studies have used satellite-derived data and found associations between higher NTL exposure and an increased risk of CVD, as well as obesity, diabetes, and hypertension.[9,13,14] A UK Biobank study using wrist-worn light sensors found NTL exposure to be a significant risk factor for CVD in adults aged ≥40 years, demonstrating a dose–response relationship.[9]

In Thailand, satellite-derived NTL data have been available since 1992 via the Defense Meteorological Satellite Program. The advent of the Suomi National Polar-orbiting Partnership satellite in 2011 substantially improved spatial resolution and radiometric sensitivity, enabling more precise detection of artificial light at night.[15,16] NTL imagery has been utilized in economics to estimate population growth and gross provincial product (GPP); however, it is rarely applied in healthcare research.[16,17]

The Health Data Center (HDC) houses a nationwide relational database with a standardized reporting system that mostly covers Ministry of Public Health (MOPH) affiliated health facilities in Thailand, including regional, general, and community hospitals; subdistrict health-promoting hospitals; and other government-affiliated facilities, covering approximately 116 tertiary hospitals, 774 secondary hospitals, and 10,174 primary care units, which together encompass more than 90% of Thailand's public-sector healthcare facilities.[18–20] Given Thailand's CVD burden, we aimed to assess the association between NTL intensity from the satellite imagery in 2010 and 2023, and the CVD admission rate in 2024, defined as the proportion of hospital admissions attributable to CVD, as reported in the HDC database among patients aged ≥40 years.

Methods

Study Design and Subjects

This ecological study utilized aggregated data on CVD admissions in 2024 of patients aged ≥40 years following approval from Thailand's MOPH. We included all inpatient encounters, which enumerates all admissions. Patients from Bueng Kan Province were excluded because the province was established in 2011, when NTL data were unavailable at that time. A total of 401,157 patient admissions were included (146,999 for HF; 37,379 for myocardial infarction (MI), 82,684 for stroke, and 134,095 for AF).

Data Collection

CVD cases were identified using International Classification of Diseases, 10th Edition (ICD-10) codes. We identified I50 admissions with HF, I21 for acute MI, I63 for cerebral infarction, and I48 for AF and atrial flutter. Unique admissions were defined by hospital code, system-generated patient ID, admission number, and admission date, then aggregated by province. The admission rate was calculated using an episode-based approach, specifically, the number of CVD admissions divided by the total number of admissions within the province, expressed as CVD admissions per 1,000 total admissions. Each admission was treated as a distinct episode; therefore, repeat admissions of the same individual on different days in 2024 were counted as separate episodes. This admission-based metric reflects the relative burden of CVD within the hospital system and facilitates comparison across provinces with differing healthcare utilization patterns.

We assessed the 2010 Location Quotient of Smoothed Nighttime Light (LQSNL) against the 2024 CVD admission rate. The 14-year lag period was selected a priori to reflect the chronic and cumulative nature of CVD development, in which long-term exposure to low-intensity environmental risk factors may take more than a decade to manifest clinically relevant differences in disease burden. This choice is supported by longitudinal evidence indicating that differences in cardiovascular risk factor profiles translate into approximately 10–15 years of variation in CVD-free survival.[21]

While NTL reflects the unadjusted average brightness, LQSNL compares a province's mean of national light to its national mean, informing whether a province is "over-lit" or "under-lit". An LQSNL value of one indicates a province with typical lighting relative to others; values less than one indicate a darker-than-average province, and values greater than one indicate a brighter-than-average province in terms of NTL. The LQSNL values for Thailand in 2010 were taken from Kekina derived from the Defense Meteorological Satellite Program.[17] The 2023 average NTL, derived from Google Earth, which uses the Suomi National Polar-orbiting Partnership satellite, was also extracted and estimated as an LQSNL for sensitivity analysis. Each province's GPP in 2023 was extracted from the Office of the National Economic and Social Development Council.[22]

Statistical Analysis

Analyses were performed using R (version 4.4.1).[23] Categorical variables were summarized using frequency and percentage and continuous variables using the mean and standard deviation. The Smoothed NTL (SNTL) from Kekina reflects Ordinary Least Squares-fitted brightness, adjusted for GPP and year (1995–2010) to calibrate brightness across satellite systems and observation periods.[17] In this framework, GPP serves as an external calibration anchor reflecting persistent human activity that is strongly correlated with true ground-level light emission, while year adjustment accounts for systematic sensor- and time-related variability. This established approach reduces measurement error in satellite-derived NTL and yields a calibrated index that more accurately represents ambient night-time light exposure. Similarly, the 2023 SNTL used in this study was adjusted for GPP and year (2014–2023). We calculated the intensity-based location quotient as the ratio of the province's log-transformed mean NTL intensity to the contemporaneous national log-transformed mean NTL. We assessed bivariate associations with scatterplots and Pearson's correlation (r), and modeled relationships with univariable and multivariable linear regression. We adjusted for the number of beds in hospitals based on available data from the Health Administration Division as hospital capacity may affect the admission rate.[24] Although MOPH hospitals exist in Bangkok, province-level bed counts corresponding specifically to facilities contributing data to the HDC were not available; therefore, the bed count for Bangkok was imputed using the mean number of beds. Furthermore, a subgroup analysis excluding Bangkok was also done. A sensitivity analysis was done using the 2023 NTL. All statistical tests were two-sided, and a p-value less than 0.05 was considered statistically significant.

Results

Descriptive Analysis of CVD Outcomes and LQSNL

There were 2,858,192 admissions in 2024. As shown in Table 1, the admission rates for HF, MI, stroke, and AF were 51.43, 13.08, 28.93, and 46.92 per 1,000 admissions, respectively. The highest admission rate across all CVD outcomes was observed in the 4th quartile of provinces with the highest LQSNL. Figure 1 shows the geographic distribution of average NTL exported from Google Earth and LQSNL. Higher nighttime brightness was concentrated in the central region and in densely populated areas of Thailand, such as Nakhon Ratchasima and Chiang Mai.

Table 1. Cardiovascular admission rates (per 1,000 admissions) by quartile of location quotient of smoothed nighttime light (LQSNL).

LQSNL	Heart failure	Myocardial infarction	Stroke	Atrial fibrillation
Overall	51.43	13.08	28.93	46.92
Quartile				
1 (0.280–0.718)	53.82 (15.39)	13.17 (7.12)	27.91 (10.65)	44.59 (8.75)
2 (0.718–0.950)	56.64 (21.38)	14.69 (8.39)	30.20 (10.00)	40.92 (8.92)
3 (0.950–1.340)	52.95 (11.78)	12.98 (4.86)	29.83 (6.75)	47.06 (6.90)
4 (1.340–2.680)	59.93 (8.04)	18.48 (5.12)	33.51 (7.37)	54.37 (8.53)

Numbers in brackets are standard deviations. LQSNL is a relative measure across provinces. LQSNL quartiles are defined by dividing provinces into four strata, with 19 provinces equally in each quartile.

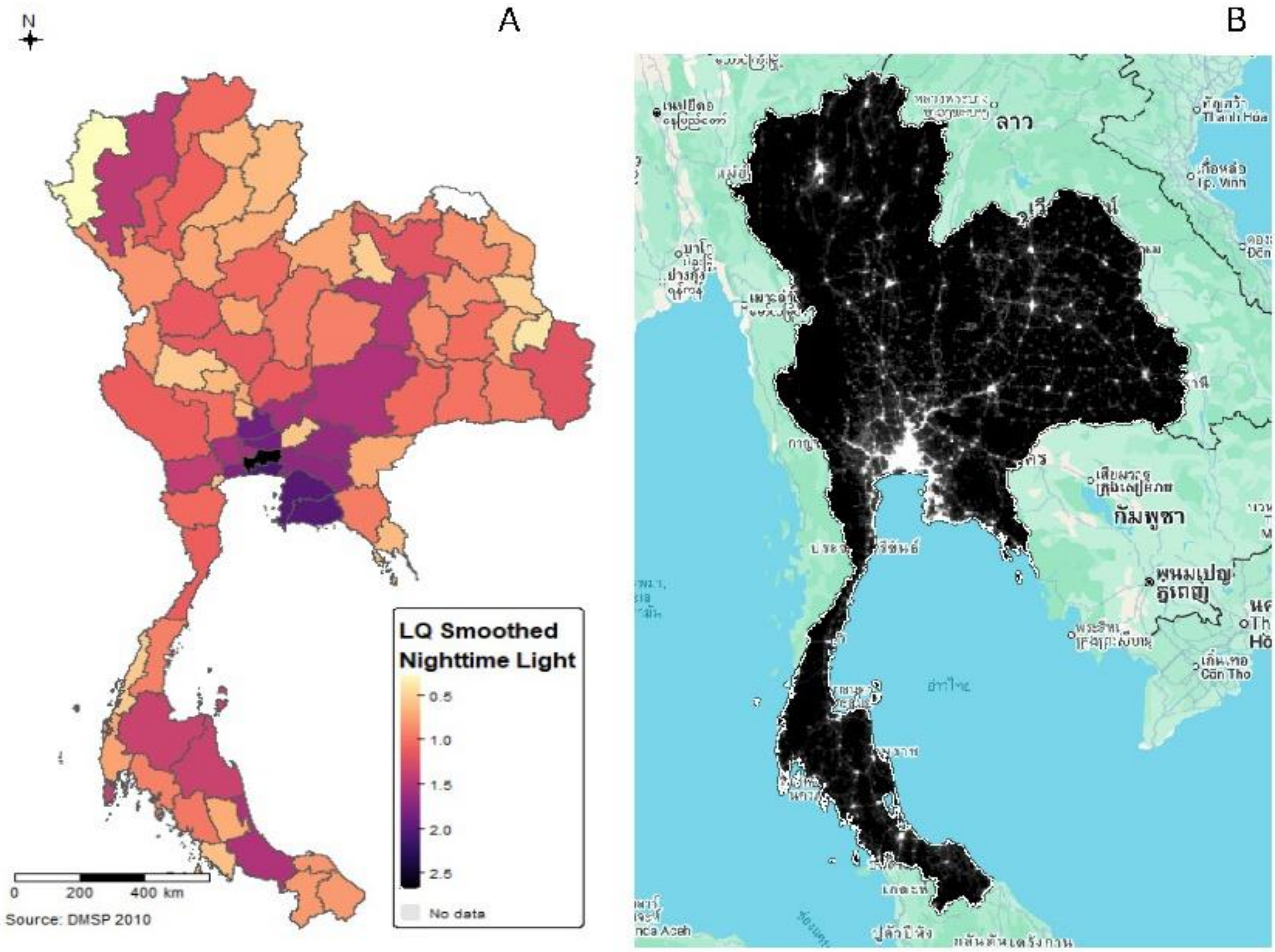

Figure 1. Geographic distribution of (A) location quotient smoothed nighttime light (LQSNL) and (B) average nighttime light in 2010 extracted from Google Earth, in which the white shaded area indicates a bright nighttime light of above 21 Digital Numbers (DNs).

Relationship between LQSNL in 2010 and CVD Admission Rates in 2024

Figure 2 shows scatterplots of LQSNL and admission rates for the four studies CVD stratified by geographical region. There were positive correlations between LQSNL values from 2010 and admission rates in 2024 for MI (*r* 0.31, *p* <0.001), stroke (*r* 0.24, *p* 0.035), and AF (*r* 0.47, *p* <0.001). A sensitivity analysis using LQSNL values from 2023 yielded similar patterns (Figure 3), including a significant correlation with heart failure admission rate (*r* 0.27, *p* 0.017). Table 2 presents the results of the univariable and multivariable linear regression models of LQSNL values in 2010 and 2023 on the four studies CVD admission rates. After adjusting for the number of hospital beds, higher LQSNL values were significantly associated with higher admission rates across all CVDs. In 2023, a 1-unit increase in LQSNL was associated with higher admission rates (estimate, 95% confidence interval) for heart failure (5.02, 0.85–9.19), myocardial infarction (3.32, 1.50–5.14), stroke (3.27, 0.73–5.80), and atrial fibrillation (6.13, 3.70–8.56). In 2010, the adjusted associations were statistically significant for all outcomes. A subgroup analysis excluding Bangkok revealed a similar pattern using both the 2010 and 2023 LQSNL data (Table 3).

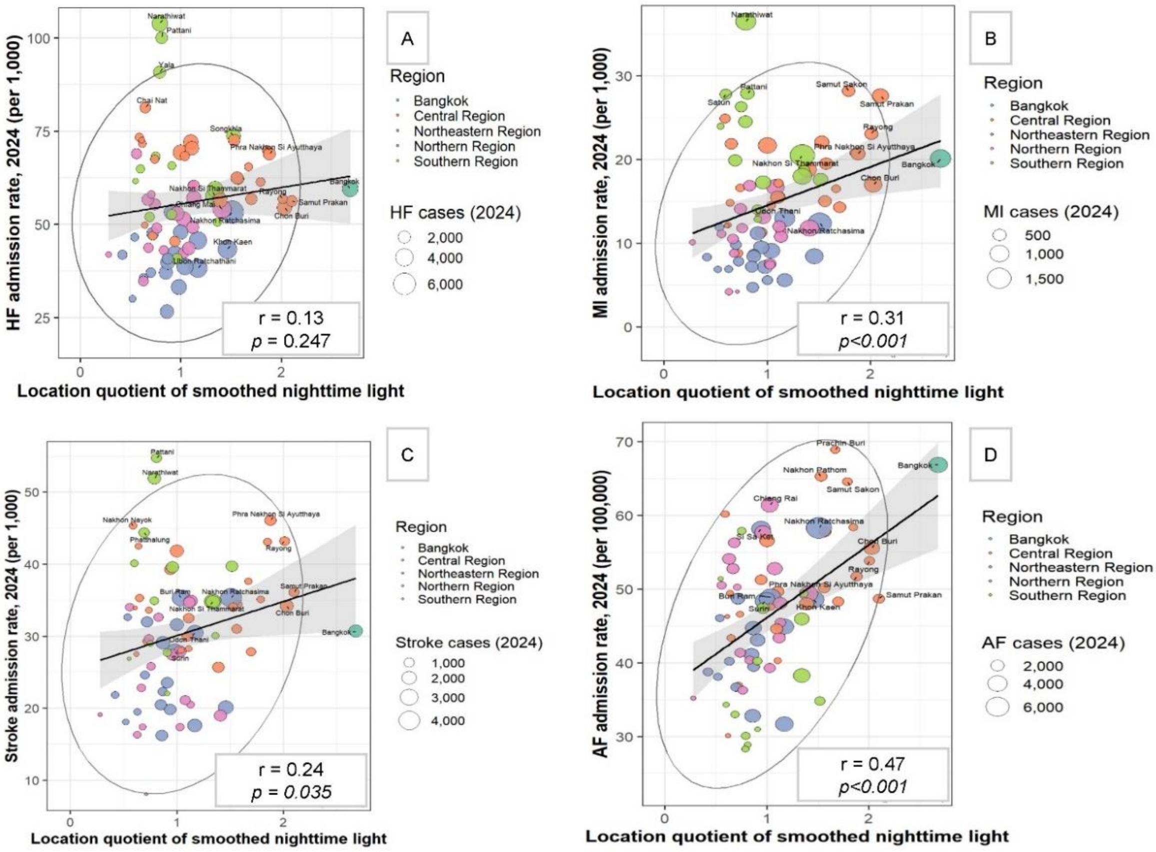

Figure 2. Scatterplots of the 2010 location quotient of smoothed nighttime light versus cardiovascular admission rates: (A) heart failure (HF), (B) myocardial infarction (MI), (C) stroke, and (D) atrial fibrillation (AF).

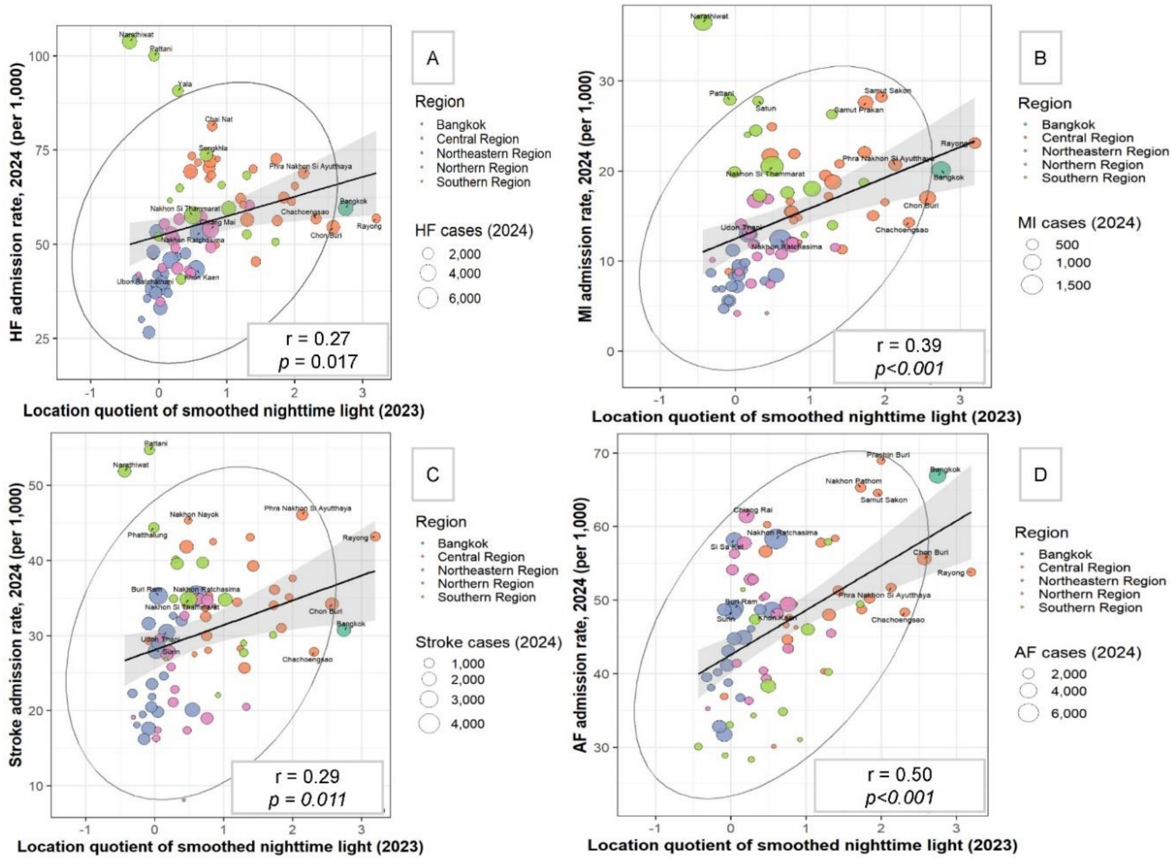

Figure 3. Scatterplots of the 2023 location quotient of smoothed nighttime light versus cardiovascular admission rates: (A) heart failure (HF), (B) myocardial infarction (MI), (C) stroke, and (D) atrial fibrillation (AF).

Table 2. Univariable and multivariable linear regression analysis of the location quotient of smoothed nighttime light and various cardiovascular disease admission rates.

Model	Year	Estimate	95% CI	Adjusted estimate*	95% CI	R^2
Heart failure						
1	2010	4.43	–3.13, 11.99	8.96	1.10, 16.82	0.12
2	2023	5.22	0.97, 9.48	5.02	0.85, 9.19	0.13
Myocardial infarction						
3	2010	4.60	1.32, 7.88	6.85	3.50, 10.20	0.22
4	2023	3.40	1.56, 5.24	3.32	1.50, 5.14	0.19
Stroke						
5	2010	4.73	0.33, 9.13	6.25	1.51, 11.00	0.09
6	2023	3.29	0.78, 5.81	3.27	0.73, 5.80	0.09
Atrial fibrillation						
7	2010	9.87	5.61, 14.13	11.02	6.39, 15.64	0.24
8	2023	6.07	3.65, 8.50	6.13	3.70, 8.56	0.26

**Adjusted for number of hospital beds. CI: confidence interval. R^2: coefficient of determination*

Table 3. Subgroup analysis of univariable and multivariable linear regression analysis of the location quotient of smoothed nighttime light (LQSNL) and various cardiovascular disease admission rates, excluding Bangkok.

Model	Year	Estimate	95% CI	Adjusted estimate*	95% CI
Heart failure					
1	2010	4.86	–3.51, 13.23	10.69	1.85, 19.53
2	2023	5.58	1.08, 10.07	5.35	0.95, 9.76
Myocardial infarction					
3	2010	4.88	1.25, 8.51	7.79	4.03, 11.55
4	2023	3.48	1.54, 5.43	3.40	1.48, 5.33
Stroke					
5	2010	5.68	0.83, 10.52	7.82	2.52, 13.13
6	2023	3.62	0.97, 6.27	3.59	0.92, 6.26
Atrial fibrillation					
7	2010	9.33	4.62, 14.04	10.65	5.42, 15.88
8	2023	5.69	3.14, 8.24	5.75	3.19, 8.30

**Adjusted for the number of hospital beds. CI: confidence interval.*

Discussion

This ecological study, to our knowledge, is the first in Thailand to examine the association between NTL intensity and CVD admission rates. We observed positive correlations across all study outcomes using both 2010 and 2023 NTL data. These findings suggest that satellite-derived NTL may serve as a useful proxy for estimating the burden of CVD admissions.

NTL data has been used as a proxy to estimate population density and urbanicity in other studies.[16,17,25,26] The positive association between NTL and CVD admissions likely reflects urbanicity. Studies have shown that urban areas exhibit higher CVD hospitalizations due to greater air pollution, limited green space, and adverse lifestyle patterns.[27,28] Geospatial analyses consistently identify hospitalization hot spots in dense districts, often with older populations and elevated pollution, where CVD mortality and admissions increase with urban density and built-environment complexity.[27,28] Moreover, hospitals in urban areas typically have more advanced services and specialist capacity. Therefore, as CVDs require specialty care, referrals concentrate these cases in urban facilities, resulting in higher observed caseloads than in non-urban settings.

Beyond its role as a proxy for urbanicity, emerging evidence suggests that NTL exposure may also act as an independent risk factor for CVD through biological pathways.[9,13,14] Experimental and epidemiologic studies indicate that exposure to artificial light at night can disrupt circadian rhythms, suppress melatonin secretion, alter sleep architecture, and affect metabolic and autonomic regulation, all of which are implicated in cardiovascular pathophysiology.[9,11] Moreover, recent individual-level studies that adjusted for demographic factors, health behaviors, shift-work status, sleep quality, and polygenic risk scores have reported associations between higher NTL exposure and an increased risk of incident CVD, supporting the plausibility of a direct effect independent of urbanicity-related factors.[9,14]

Satellite-derived NTL in Thailand has previously been shown to serve as an indicator and to efficiently predict future GPP and municipal tap-water use.[16,17] Moreover, NTL could also be used to estimate infectious disease mortality, as it may reflect denser populations and increased human activity.[25,26] However, predicting non-communicable disease admission rates may require combining it with demographic, environmental, and health-related covariates. Because patterns vary over time and space (e.g., treatments, policy shifts), models must be calibrated to the specific period and locale.[25,29]

A study from the United Kingdom (UK) used individual NTL data from a wrist-worn light sensors and found associations between higher NTL exposure and an increased risk of CVD.[9] Although smartwatches and other wearables are increasingly adopted in Thailand, only a few Thai studies have utilized them to assess health-related outcomes, and most were single-center studies.[30–32] Thailand conducts several large national surveys; however, data from wearable devices, measuring for example steps, light exposure, and heart rate variability, are not yet routinely collected.[33,34] Device-based monitoring of individual data looms an opportunity for Thailand to catch up with other countries; for example, in the UK, the UK Biobank study mailed participants a wrist-worn activity tracker for a one-week period.[9] Another option is to use satellite imagery to assign household-level NTL intensity to individuals; however, this still does not accurately capture true personal light exposure.[14]

Contemporary health research is increasingly data-rich, leveraging satellite-derived metrics to assess population risk.[35–37] Beyond NTL, sources such as mobility data, land-surface temperature, air quality, and vegetation indices provide fine-grained proxies of environmental and behavioral determinants, which have been widely applied during the COVID-19 pandemic to quantify movement and policy effects.[37] Integrating these streams with clinical records may enable more precise surveillance and targeted interventions.

Limitations

This study has several limitations. First, it is ecological in nature; associations between province-level NTL intensity and CVD admission rates cannot be assumed to apply at the individual level. Second, NTL at the provincial level serves as a proxy for urbanicity and socioeconomic activity; consequently, observed associations may reflect residual confounding by healthcare access, diagnostic intensity, and service availability, which are typically more prevalent in provinces with higher degrees of urbanicity. Nevertheless, we adjusted for the number of hospital beds by province, which revealed similar results. Furthermore, admission-based outcomes reflect a system-level burden rather than true population-level incidence, which may limit direct interpretation of disease occurrence across provinces. Third, SNTL represents a calibrated NTL index rather than raw satellite radiance. Accordingly, it should be interpreted as a relative measure of ambient NTL exposure across provinces, enabling valid spatial and temporal comparisons rather than as an absolute physical light unit. Although the calibration procedure—using GPP as an adjustment variable—reduces sensor- and time-related measurement error, some residual misclassification of environmental light exposure independent of economic activity may persist, potentially reflecting intrinsic province-specific characteristics such as cultural practices, transportation patterns, and geographic variation. Fourth, residential addresses in the administrative database may be outdated or inaccurate, leading to exposure misclassification. Finally, measurement error in satellite-derived light (e.g., sensor, atmospheric, or compositing artifacts) and potential temporal mismatch between exposure year and outcome year could further attenuate or distort effect estimates. However, several statistical adjustments were made to account for GPP and temporal mismatch. We did not evaluate the true incidence of admission; future prospective cohort studies that follow individuals from a pre-CVD baseline to incident CVD would be highly informative.

Public Health Recommendations

This study provides preliminary evidence, using nationwide publicly available data, of a positive association between NTL and various CVD admission rates, paving the way for future work that utilizes individual-level NTL data and includes exogenous variables in Thailand, as well as extending to other diseases.

Conclusion

This study, to our knowledge, is the first in Thailand to reveal that higher NTL intensity is consistently associated with higher provincial admission rates for major cardiovascular conditions, using both historical (2010) and contemporary (2023) NTL data. The findings support the use of satellite-derived NTL as a practical proxy for population density, urbanicity, and healthcare demand, with potential applications in surveillance and resource planning. Given the study's ecological design and potential residual confounding, future work should incorporate individual-level exposures (e.g., wearable light data) and additional demographic, environmental, and health system covariates to refine risk estimates and assess causality.

Acknowledgements

The authors thank all staff members of the Ministry of Public Health, Nonthaburi, Thailand, for their support in completing the current study.

Authors Contributions

Sethapong Lertsakulbunlue: Conceptualization, data curation, formal analysis, methodology, writing—original draft, writing—review & editing, project administration, resources, validation, visualization. **Rapeepong Suphanchaimat:** Conceptualization, supervision, methodology, writing—review & editing, validation. **Pitiphon Promduangsi:** Supervision, writing—review & editing, validation.

Ethical Approval

As part of the Department of Disease Control's situation assessment (Ministry of Public Health, Thailand), this study utilized publicly accessible Google Earth data and approved, anonymized records from the HDC. Ethics approval was not required.

Informed Consent

Patient informed consent was waived because this study used secondary data from the HDC, in which all records were anonymized prior to analysis. The research involved no direct contact with participants and posed minimal risk. Obtaining individual informed consent was not feasible given the large number of records and the retrospective nature of the data.

Data Availability

Data cannot be shared publicly because the data belongs to the HDC, MOPH. Data are available from the MOPH in Nonthaburi, Thailand, for researchers who meet the criteria to access confidential data.

Conflicts of Interest

The author declares that they no conflicts of interests.

Funding Support

The authors declare that they received no funding support.

Declaration of Generative-AI and AI-assisted Technologies in the Writing Process

We utilized ChatGPT-5.0 to assist with correcting the grammar in the manuscript. The authors remain fully responsible for the accuracy and integrity of the content.

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