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NEW CHALLENGES FOR CITIES IN THE TWENTY-FIRST CENTURY

Regenerative Design - Climate Adaptation & Mitigation
Circular Economy - Citizen Agency - Urban Livability

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Assessing urban growth and pollution through nightlight data: a case study in Thailand

Linking urban growth and CO concentrations via nightlights

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Abstract
This study explores the relationship between urban development and air pollution in Thailand by analyzing remote sensing nightlight data and carbon monoxide (CO) concentrations over six years (2019-2024). Using data from VIIRS Day/Night Band (DNB) satellite imagery, CO levels, electricity consumption, and lignite production, the study finds a significant positive correlation (Pearson coefficient = 0.586) between nightlight intensity and CO concentrations. This suggests that nightlight data can be an effective tool for monitoring urban-related pollution. Seasonal and regression analyses show that urban growth contributes to pollution, but this is influenced by seasonal patterns and energy consumption. Multiple regression models highlight nightlight intensity as the strongest predictor of CO levels, with energy factors adding significant explanatory power. Regional analysis identifies the Bangkok Metropolitan Region as having the highest nightlight intensity and CO levels (correlation = 0.598). Lag correlation analysis suggests that changes in CO and nightlight intensity are most strongly correlated at zero lag, with CO changes slightly leading in some areas. These findings have implications for urban planning, environmental policy, and public health in Southeast Asia.

Keywords
Nightlight remote sensing; Seasonal patterns; Urban air pollution; Urban planning; VIIRS data

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1. Introduction

Rapid urbanization across Southeast Asia has led to significant environmental challenges, particularly regarding air quality and public health. Thailand, as one of the region's most dynamic economies, represents an ideal case study for examining the complex relationship between urban development and environmental quality. As cities expand, the demand for energy and transportation grows, often outpacing the development of sustainable infrastructure.

To monitor these dynamics, the scientific community has increasingly turned to remote sensing technologies. Traditional monitoring methods often rely on ground-based data that may be inconsistent, delayed, or insufficient in temporal and spatial resolution. In contrast, satellite-derived nightlight data has emerged as a robust proxy for anthropogenic activity, establishing a continuity of research that links luminous intensity to various socioeconomic indicators. Since the pioneering work of Elvidge et al. (2017), nightlight imagery has been extensively validated for estimating economic activity (Chen & Nordhaus, 2011), population distribution, and energy consumption (Li et al., 2020).

More recently, the application of nightlight data has expanded to environmental monitoring. Previous studies have demonstrated strong correlations between nightlights and various pollutants. For instance, Wang et al. (2019) utilized VIIRS data to predict air pollutants such as Nitrogen Dioxide (NO_2) and particulate matter (PM2.5) in urban environments. Similarly, Zuo et al. (2022) investigated the relationship between nightlights and Carbon Dioxide (CO_2) emissions, highlighting how industrial structures influence these correlations. However, despite these advancements, there remains a significant gap in the literature. Few studies have explored the specific spatiotemporal dynamics of Carbon Monoxide (CO) in developing tropical economies, particularly when analyzing the mediating role of specific fuel types like lignite.

This study addresses this gap by proposing an integrated analytical framework that links human activity indicators, atmospheric observations, and energy-system indicators. We use the VIIRS Stray Light Corrected Nighttime Day/Night Band Composites Version 1 (VCMSLCFG) and focus on the monthly mean radiance variable avg_rad, which represents average nighttime top-of-atmosphere radiance derived from cloud-free observations at a spatial resolution of 463.83 m. Although stray-light correction improves data usability, particularly at higher latitudes, avg_rad may still reflect transient illumination and background signals and therefore is interpreted as an indirect reflection of aggregate human activity rather than a direct measure of urban lighting intensity.

We integrate these nightlight-derived indicators with Sentinel-5P TROPOMI Carbon Monoxide (CO) observations to examine how the spatial and temporal rhythms of human activity drive atmospheric pollution. To disentangle these emission drivers, we combine remote-sensing metrics with ground-based energy statistics, including electricity consumption and lignite production. Within this framework, nightlights represent the demand side of urban and economic activity, while energy production and consumption capture the supply side of emissions, enabling a more comprehensive assessment of how urban development and pollution are fundamentally intertwined.

Therefore, the primary objective of this research is to quantify the relationship between urban development and CO concentration.

This research addresses several key questions:

- What is the relationship between nightlight intensity and CO concentrations in Thailand?
- How do seasonal and annual patterns affect this relationship?
- To what extent do electricity consumption and lignite production influence both nightlight intensity and CO levels?
- Can nightlight data serve as an effective proxy for monitoring urban-related pollution?
- How do regional and provincial differences affect the relationship between nightlight intensity and CO concentrations?

By addressing these questions, this study contributes to a growing body of literature on remote sensing applications for environmental monitoring and provides valuable insights for urban planners and policymakers in Thailand and comparable developing economies.

2. Data and methodology

2.1 Data sources

This study utilizes monthly data from January 2019 to December 2024 for Thailand, covering all 77 provinces, and comprising four primary variables:

Nightlight intensity

Mean nightlight values were derived from the VIIRS Stray Light Corrected Nighttime Day/Night Band Composites Version 1 (VCMSLCFG), accessed through Google Earth Engine (Hankey & Marshall, 2017). This product provides a monthly cloud-free composite of nighttime lights at 463.83 m spatial resolution with improved calibration and stray light correction, making it superior to earlier DMSP/OLS data for quantitative analysis of nighttime light emissions (Elvidge et al., 2017).

Our processing workflow consisted of the following steps:

1. Data Acquisition: Monthly nightlight composites were obtained for Thailand using the official administrative boundary from the USDOS/LSIB database, ensuring precise spatial delineation of the study area. Fig.1 presents VIIRS-derived nightlight intensity across Thailand (2022). The bright yellow-white area in the central region corresponds to the Bangkok Metropolitan Region, with smaller urban centers visible as blue points throughout the country. White boundary lines indicate provincial borders. Nightlight intensity serves as a proxy for urban development and human activity.

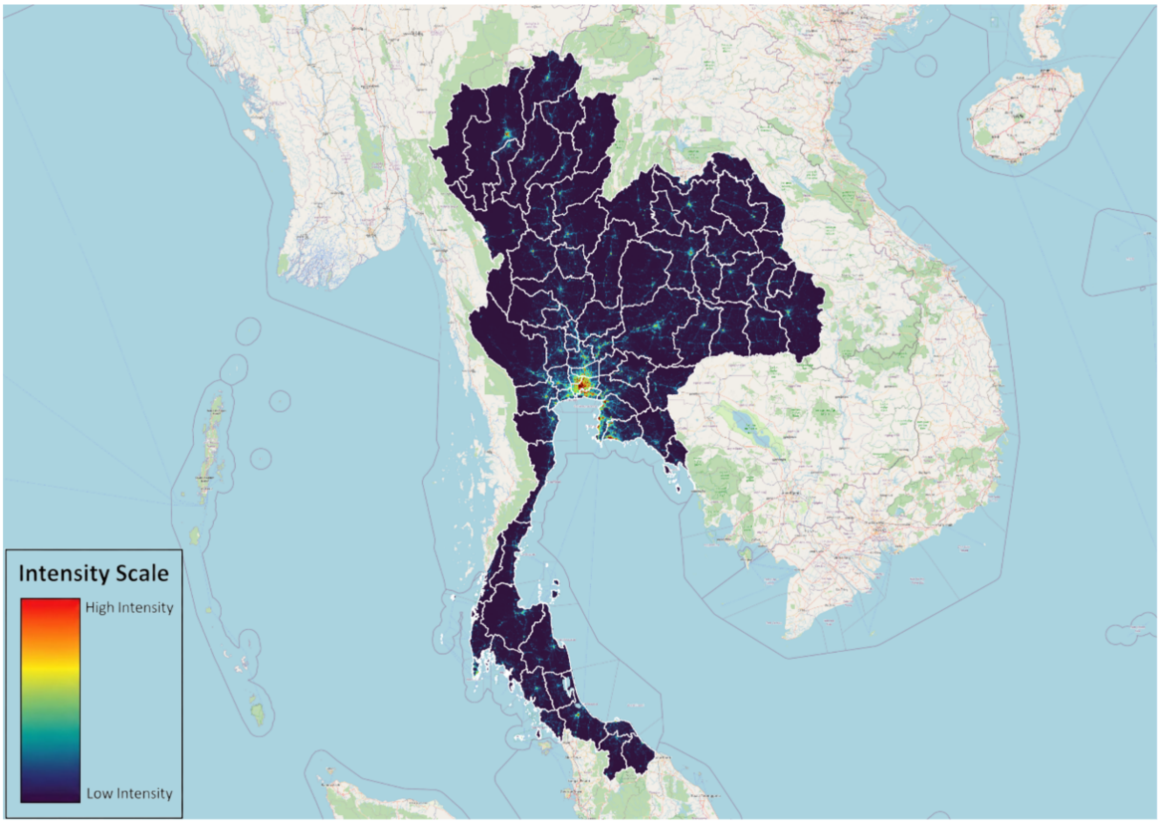

Fig.1 VIIRS-derived nightlight intensity across Thailand (2022)

2. Quality Filtering: To ensure data quality, we applied a pixel-level quality control filter using the QF_Cloud_Mask band. Only pixels flagged as "confident clear" (bitmask value 0) were retained, while cloudy or degraded pixels were masked out;
3. Radiance Selection: We extracted the "avg_rad" band, which represents the average radiance values measured in nanoWatts/sr/cm2, providing a consistent metric of nighttime light intensity;
4. Temporal Aggregation: For each month in the study period from January 2019 to December 2024, we calculated the median value to reduce the influence of outliers and short-lived illumination. The median was preferred over the mean because it is less sensitive to transient extreme values and residual stray light effects;
5. Spatial Aggregation: The final monthly nightlight value for each province was calculated as the spatially weighted mean of all valid pixels within the provincial boundary, automatically handling missing data by excluding masked pixels from the calculation;
6. National Averaging: The final monthly nightlight value for Thailand was calculated as the area-weighted mean radiance across all valid pixels within the country's boundary.

The resulting nightlight intensity metric serves as a proxy for urban development and human activity, capturing both the spatial extent and intensity of artificial lighting. This approach enables consistent monitoring of urbanization patterns throughout our study period, with values ranging from 0.318 to 1.347 nanoWatts/sr/cm^2 for national monthly averages.

CO concentrations

Mean atmospheric carbon monoxide measurements were derived from the Sentinel-5P NRTI CO: Near Real-Time Carbon Monoxide product. To ensure high data fidelity, we filtered the TROPOMI data using the provided qa_value (quality assurance value). Following product recommendations, we excluded all pixels with a qa_value < 0.5, which effectively removes data degraded by thick clouds or retrieval errors (Borsdorff et al., 2019).

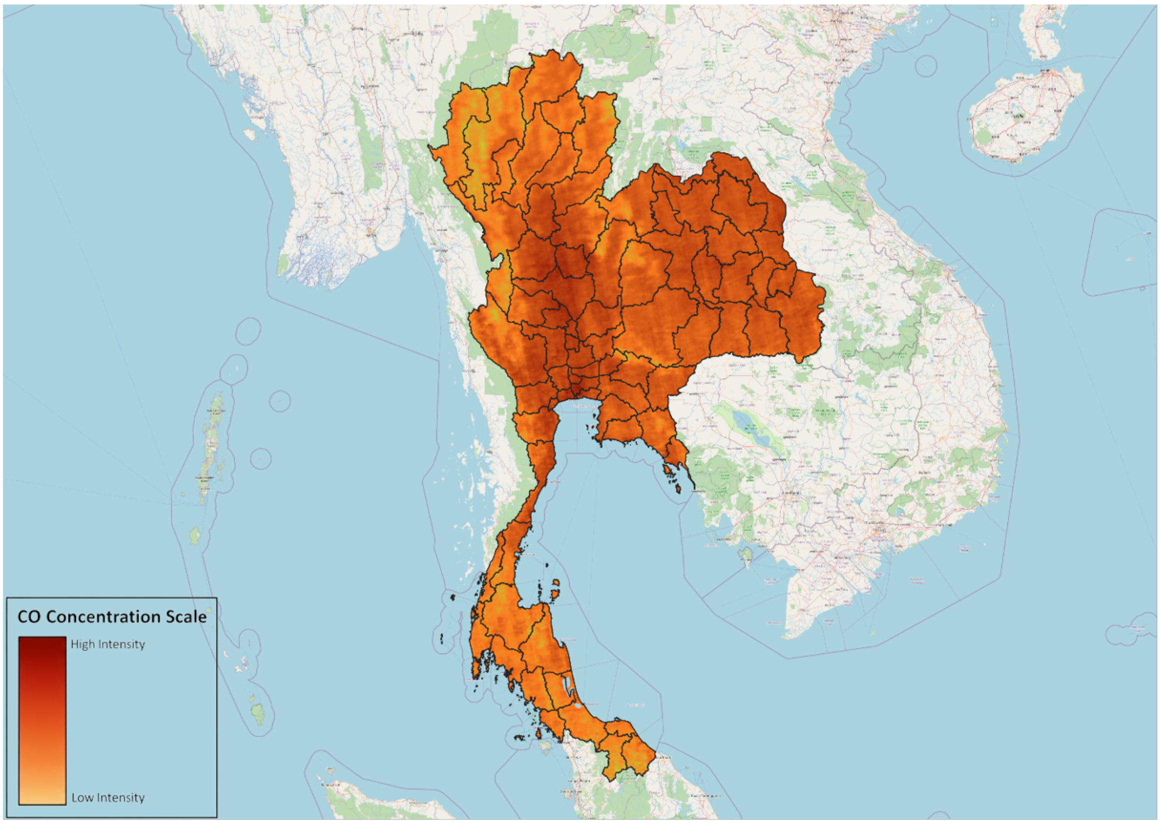

Fig.2 Carbon monoxide (CO) concentrations across Thailand derived from Sentinel-5P TROPOMI data (2022)

Spatially, we aggregated the valid 1 × 1 km pixels to the provincial level using a mean reduction method. In cases where pixels partially overlapped provincial borders, an area-weighted average was applied to assign values to the respective administrative units. The product measures the total column of CO (mol/cm^2). The satellite-based approach provides consistent spatial coverage across Thailand and captures CO from all sources, including transportation, industrial processes, biomass burning, and residential fuel combustion (Landgraf et al., 2016).

Fig.2 presents Carbon monoxide (CO) concentrations across Thailand derived from Sentinel-5P TROPOMI data (2022). Orange-red areas indicate higher CO concentrations, with darker red showing the highest levels. The distribution pattern shows correlation with urban centers and transportation corridors, with particularly elevated levels in the northern region during the dry season.

Electricity consumption

Monthly electricity consumption data for Thailand were obtained from the Electricity Generating Authority of Thailand (EGAT). These data represent total national consumption measured in gigawatt-hours (GWh), providing an indicator of energy usage patterns that may correlate with both urban activity and pollution generation.

Lignite production and consumption

Monthly data on the production and consumption of lignite, a primary fossil fuel used in Thailand's electricity generation, were sourced from the Department of Mineral Resources. Lignite is a low-grade coal that, when burned, can be a significant source of various pollutants, including carbon monoxide, particularly if combustion processes are inefficient.

2.2 Analytical methods

The analytical approach employed in this study consists of several complementary methods designed to explore the relationship between nightlight intensity and CO concentrations, while accounting for potential mediating factors and temporal dynamics.

Correlation analysis

Pearson correlation coefficients were calculated to quantify the strength and direction of relationships between key variables, with particular focus on the association between nightlight intensity and CO concentrations. The Pearson correlation coefficient (r) between two variables X and Y is calculated as shown in Equation (1).

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2}\sqrt{\sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2}} \tag{1}$$

Where:

- r is the Pearson correlation coefficient;
- X_i is the i-th observation of variable X;
- Y_i is the i-th observation of variable Y;
- $\bar{X}$ is the mean value of variable X;
- $\bar{Y}$ is the mean value of variable Y;
- n is the total number of paired observations.

Additional correlations between these primary variables and electricity consumption and lignite production were also analyzed to identify potential mediating relationships. A correlation matrix was generated to visualize the network of relationships among all variables in the dataset.

Time series analysis

Time series decomposition was applied to both nightlight intensity and CO concentration data to separate the underlying trend, seasonal patterns, and residual components. We employed the additive decomposition model, as shown in Equation (2).

$$Y_t = T_t + S_t + R_t \tag{2}$$

Where:

- Y_t is the observed value of the time series at time t;
- T_t is the trend component of the time series at time t, representing the long-term progression;
- S_t is the seasonal component at time t, capturing periodic fluctuations;
- R_t is the residual component at time t, representing irregular variations not explained by the trend or seasonal structure.

This approach enables a clearer understanding of long-term trajectories versus seasonal variations in both urban development and pollution levels. The seasonal component S_t was modeled using month-specific coefficients that capture the cyclical nature of both variables. Additionally, we analyzed annual trends by calculating yearly averages for each variable and examined monthly patterns by aggregating data across years for each month.
To measure the proportion of variance explained by seasonality for each variable, we used the variance ratio, as shown in Equation (3).

$$VR_{seasonal} = \frac{\sum_{t=1}^{T}(S_t)^2}{\sum_{t=1}^{T}(Y_t)^2} \tag{3}$$

Where:

- $VR_{seasonal}$ is the variance ratio representing the proportion of total variance in the time series;
- S_t is the seasonal component at time t, capturing periodic fluctuations;
- Y_t is the observed value of the time series at time t;
- T is the total number of time steps in the time series.

This ratio quantifies the relative contribution of seasonal patterns to the overall variability in the time series data.

Regression analysis

Two regression models were developed to quantify the relationship between nightlight intensity and CO concentrations:

1. Simple Linear Regression: Modeling CO concentrations as a function of nightlight intensity alone to establish the baseline relationship, as shown in Equation (4).

$$CO_t = \beta_0 + \beta_1 \cdot Nightlight_t + \epsilon_t \tag{4}$$

Where:

- CO_t is the carbon monoxide concentration at time t;

- β_0 is the intercept term of the regression model;
- β_1 is the regression coefficient representing the effect of nightlight intensity on CO concentration;
- $Nightlight_t$ is the nightlight intensity at time t;
- t is the error term at time t capturing unexplained variation in CO concentration.

2. Multiple Regression: Incorporating electricity consumption and lignite production as additional predictors to assess their mediating influence, as shown in Equation (5).

$$CO_t = \beta_0 + \beta_1 \cdot Nightlight_t + \beta_2 \cdot Electricity_t + \beta_3 \cdot Lignite_t + \epsilon_t \tag{5}$$

Where:

- CO_t is the carbon monoxide concentration at time t;
- β_0 is the intercept term of the regression model;
- β_1 is the regression coefficient associated with nightlight intensity;
- β_2 is the regression coefficient associated with electricity consumption;
- β_3 is the regression coefficient associated with lignite production;
- $Nightlight_t$ is the nightlight intensity at time t;
- $Electricity_t$ is the electricity consumption at time t;
- $Lignite_t$ is the lignite production at time t;
- ϵ_t is the error term at time t capturing unexplained variation in CO concentration.

For both models, we calculated standard regression diagnostics including R-squared values, adjusted R-squared, coefficient significances, and standardized coefficients to facilitate comparison of the relative importance of different predictors.

Lag correlation analysis

Lag correlation analysis was conducted to examine the potential temporal relationships between nightlight intensity and CO concentrations. This approach tests how past values of one variable relate to current values of another, helping to understand lead-lag relationships between variables. For a lag k, the correlation between X_{t-k} and Y_t was calculated to determine if changes in one variable tend to precede changes in another, as shown in Equation (6).

$$r_k = \frac{\sum_{t=k+1}^{T}(X_{t-k} - \bar{X})(Y_t - \bar{Y})}{\sqrt{\sum_{t=k+1}^{T}(X_{t-k} - \bar{X})^2}\sqrt{\sum_{t=k+1}^{T}(Y_t - \bar{Y})^2} \tag{6}$$

Where:

- r_k is the Pearson correlation coefficient at lag k;
- X_{t-k} is the value of variable X at time $t-k$;
- Y_t is the value of variable Y at time t;
- $\bar{X}$ is the mean of variable X over the analysis period;
- $\bar{Y}$ is the mean of variable Y over the analysis period;
- k is the lag length expressed in time steps;
- T is the total number of time steps in the time series.

We calculated lag correlations for lag k ranging from 0 to 6 months in both directions (nightlight leading CO and vice versa). The statistical significance of the lag correlation coefficients (r_k) was assessed using a t-test. The null hypothesis (H_0: r_k = 0) was tested with T - k - 2 degrees of freedom, where T is the total number of time periods, as shown in Equation (7).

$$t = \frac{r_k\sqrt{T-k-2}}{\sqrt{1-r_k^2}} \tag{7}$$

Where:

- t is the test statistic used to assess the statistical significance of the lag correlation coefficient;
- r_k is the lagged Pearson correlation coefficient at lag k;
- k is the lag length expressed in time steps;
- T is the total number of time periods in the time series.

Regional and provincial analysis

To account for spatial heterogeneity, we conducted analyses at both regional and provincial levels using a hierarchical spatial modeling approach:

1. Regional Analysis: Thailand was divided into five regions (Bangkok Metro, Northern, Northeastern, Central, and Southern), and correlations between nightlight intensity and CO were calculated for each region (Uttamang et al., 2018). To account for spatial autocorrelation within regions, we employed a spatial autoregressive model with the following form, as shown in Equation (8).

$$CO_i = \beta_0 + \beta_1 \cdot Nightlight_i + \rho \sum_{j=1}^{n} w_{ij} CO_j + \epsilon_t \tag{8}$$

Where:

- CO_i is the carbon monoxide concentration in spatial unit i;
- CO_j is the carbon monoxide concentration in neighboring spatial unit j;
- β_0 is the intercept term of the regression model;
- β_1 is the regression coefficient associated with nightlight intensity;
- $Nightlight_i$ is the nightlight intensity in spatial unit i;
- ρ is the spatial autoregressive parameter;
- w_{ij} is the spatial weight reflecting the spatial relationship between spatial units i and j;
- n is the total number of spatial units included in the analysis;
- ϵ_t is the error term associated with spatial unit t, capturing unexplained variation.

2. Provincial Analysis: In-depth analysis was conducted for key provinces, including Bangkok, Samut Prakan, Nonthaburi, Pathum Thani, Nakhon Ratchasima, Chiang Mai, and Songkhla, representing different regions and levels of urbanization. For each province, we constructed time series models that account for both temporal autocorrelation and seasonal effects.

3. Results

3.1 Descriptive statistics

Tab.1 presents descriptive statistics for the four primary variables analyzed in this study, covering the period from January 2019 to December 2024. The data show considerable variation in all variables over the study period, reflecting both seasonal cycles and longer-term trends.

CO concentrations show significant variability, with values ranging from 0.023581 to 0.051766 mol/m^2. This range represents an approximately twofold difference between minimum and maximum observed concentrations, underscoring the dynamic nature of this pollutant.

The mean concentration is 0.037535 mol/m^2.

Variable	Mean	Std Dev	Min	Max	Range
CO Mean (mol/m^2)	0.038	0.008	0.024	0.052	0.028
Nightlight Mean*	1.003	0.254	0.318	1.347	1.028
Electricity Cons. (GWh)	15,840	1,093	13,619	18,621	5,002
Lignite Production (thousand tons)	1,125	109	942	1,341	399

Tab.1 Descriptive Statistics of Key Variables (January 2019 - December 2024) *Measured in nanoWatts/sr/cm^2

3.2 Correlation analysis

The weighted Pearson correlation coefficient between monthly mean CO concentration and nightlight intensity was 0.586 (p < 0.001), indicating a strong positive relationship between these variables. This finding suggests that areas with higher nightlight intensity—representing greater urbanization and human activity—tend to exhibit higher levels of CO in the atmosphere. The correlation remains robust when controlling for spatial autocorrelation using Moran's I test (I = 0.428, p < 0.001), confirming that the relationship is not merely an artifact of spatial clustering.

The correlation matrix for all variables is presented in Table 2, revealing additional relationships:

Variable	CO	Nightlight	Electricity	Lignite
CO Mean	1.000	0.586	0.475	0.382
Nightlight Mean	0.586	1.000	0.535	0.318
Electricity Cons.	0.475	0.535	1.000	0.430
Lignite Production	0.382	0.318	0.430	1.000

Tab.2 Correlation Matrix of Key Variables

These findings suggest that energy consumption patterns play a role in mediating the relationship between urban development and air pollution. The stronger correlation between nightlight intensity and CO concentrations (0.586) compared to the correlations between energy variables and CO (0.475 for electricity, 0.382 for lignite) suggests that nightlight intensity captures aspects of urban development beyond energy consumption that contribute to pollution, such as transportation and industrial activities.

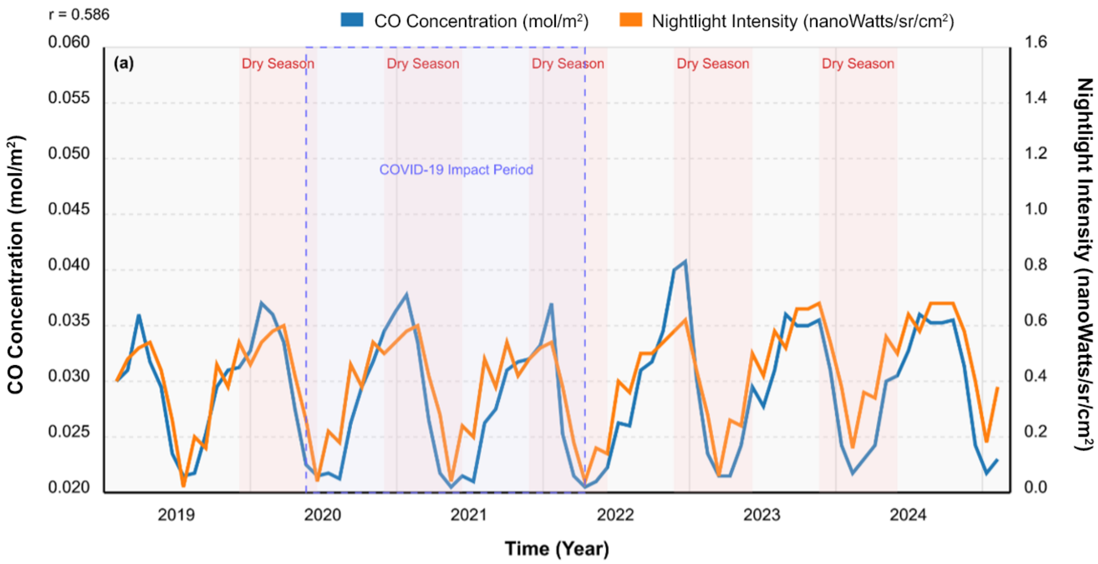

Fig.3 Time series of CO concentrations and nightlight intensity in Thailand from January 2019 to December 2024

Fig.3 presents the time series of CO concentrations and nightlight intensity in Thailand from January 2019 to December 2024. Both variables show pronounced seasonal patterns, with CO peaking during dry season months (January-April) and nightlight intensity showing peaks during December-January and April, visually illustrating their relationship over the study period. The correlation is evident in the general alignment of peaks and troughs, though not all fluctuations coincide precisely.

3.3 Temporal patterns

Seasonal variations

Both CO concentrations and nightlight intensity displayed clear seasonal patterns, but with notable differences in their cycles. Fig.4 shows the average values for each variable by month, aggregated across the six-year study period.

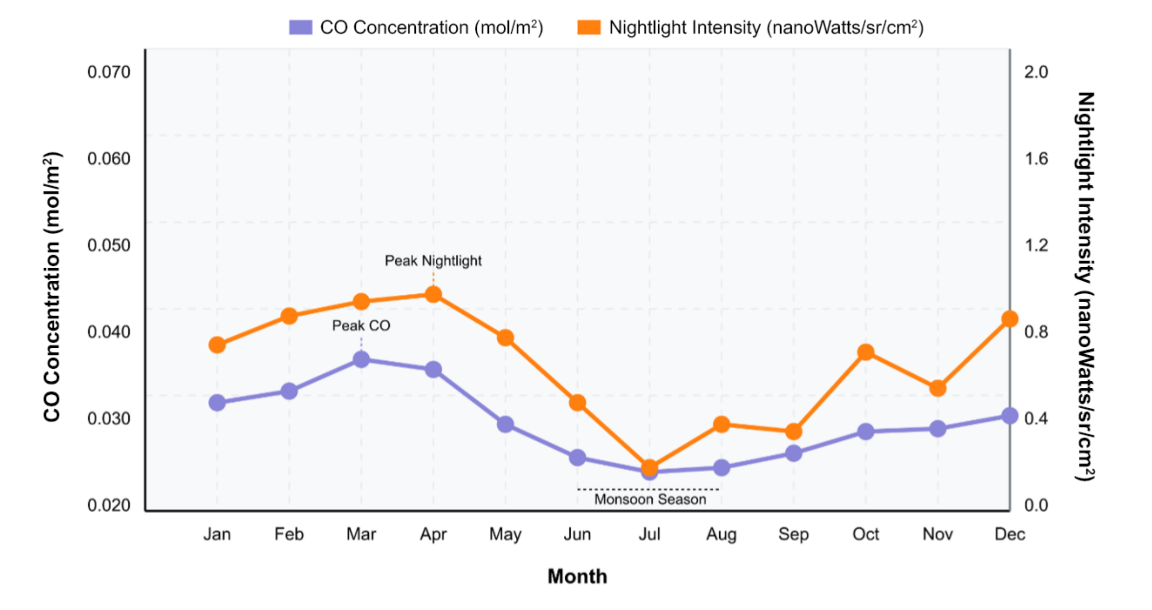

Fig.4 Monthly seasonal patterns of CO concentrations and nightlight intensity in Thailand (2019-2024 average)

Fig.4 presents the monthly seasonal patterns of CO concentrations and nightlight intensity in Thailand (2019-2024 average). Both variables show distinct seasonality with peaks in the dry season (December-April) and troughs during the wet season (May-October).

The seasonal patterns reveal that:

- CO concentrations peaked during the dry season (January-April), with the highest average value in March (0.051766 mol/m^2), and reached their lowest levels during the wet season (June-September), with the minimum in July (0.025583 mol/m^2). This pattern is consistent with established knowledge about carbon monoxide in Thailand, where dry season conditions favor pollutant accumulation due to reduced atmospheric mixing and increased biomass burning in surrounding rural areas;
- Nightlight intensity showed maximum values during December-April (peaking at 1.346730 nanoWatts/sr/cm^2 in April), coinciding with holiday celebrations, tourist season, and Thai New Year, and minimum values in July (0.531941 nanoWatts/sr/cm^2) during the monsoon season when cloud cover is most prevalent;
- Electricity consumption exhibited less pronounced seasonality but tended to be higher during the hot season (March-June) when air conditioning usage increases;
- Lignite production showed relatively modest seasonal variation, with slightly higher values in the first half of the year.

The seasonal decomposition revealed that approximately 26% of the variation in CO concentrations and 19% of the variation in nightlight intensity could be attributed to seasonal factors.

Annual trends

Over the six-year period studied (2019-2024), both variables showed overall increasing trends with some year-to-year variations. Table 3 presents the annual averages for each variable.

Variable	CO Mean (mol/m^2)	Nightlight Mean	Electricity Cons.	Lignite Production
2019	0.038993	0.898589	15,713	1,161
2020	0.037513	0.960358	15,246	1,133
2021	0.036304	1.001512	15,730	1,184
2022	0.034153	0.929382	16,080	1,145
2023	0.038068	1.215768	16,671	1,066
2024	0.036678	1.097661	16,005	958

Tab.3 Annual Average Values of Key Variables (2019-2024)

The annual trends indicate that:

- CO concentrations showed fluctuating patterns, with a notable decrease during 2021-2022 (possibly attributable to reduced activity during the COVID-19 pandemic recovery period) followed by an increase in 2023;
- Nightlight intensity increased by approximately 22% over the six-year period, with the highest values recorded in 2023, suggesting continuous urbanization even during periods of economic disruption.
- Electricity consumption showed a steady increasing trend, with a slight decrease in 2020 during the COVID-19 pandemic;
- Lignite production exhibited a declining trend, particularly pronounced in 2023-2024, potentially reflecting Thailand's energy transition policies.

The divergence between trends during 2020-2022 highlights the complex relationship between human activity, economic development, and environmental impacts, with pollution potentially responding more directly to economic slowdowns than does urbanization as measured by nightlight intensity.

3.4 Regression analysis

Simple linear regression

The simple linear regression model using nightlight intensity to predict CO concentrations yielded the following equation, as shown in Equation (9).

$$CO_t = 0.022641 + 0.014070 \cdot Nightlight_t \tag{9}$$

Where:

- CO_t is the carbon monoxide concentration at time t;
- $Nightlight_t$ is the nightlight intensity at time t;
- 0.022641 is the estimated intercept of the regression model;
- 0.014070 is the estimated regression coefficient.

This model produced an R^2 value of 0.343, indicating that nightlight intensity alone explains approximately 34.3% of the variation in CO levels. The coefficient for nightlight intensity was positive and statistically significant (p < 0.001), confirming the strong relationship identified in the correlation analysis.

Multiple regression

The incorporation of electricity consumption and lignite production into a multiple regression model produced the following equation, as shown in Equation (10).

$$CO_t = -0.019 + 0.012 \cdot Nightlight_t + 1.38 \times 10^{-6} \cdot Electricity_t + 1.62 \times 10^{-5} \cdot Lignite_t \quad (10)$$

Where:

- CO_t is the carbon monoxide concentration at time t;
- $Nightlight_t$ is the nightlight intensity at time t;
- $Electricity_t$ is the electricity consumption at time t;
- $Lignite_t$ is the lignite production at time t;
- -0.019 is the estimated intercept of the regression model;
- 0.012 is the estimated regression coefficient associated with nightlight intensity;
- 1.38×10^{-6} is the estimated regression coefficient associated with electricity consumption;
- 1.62×10^{-5} is the estimated regression coefficient associated with lignite production.

This model increased the R^2 value to 0.527, suggesting that these energy-related factors explain an additional 18.4% of the variation in CO concentrations beyond what is captured by nightlight intensity alone. Table 4 summarizes the results of both regression models.

Model	Variable	Coefficient	p-value	Std. Coef
Simple	Constant	0.023	< 0.001	-
	Nightlight Mean	0.014	< 0.001	0.586
Multiple	Constant	-0.019	0.018	-
	Nightlight Mean	0.012	< 0.001	0.498
	Electricity Cons.	1.38×10^{-6}	0.006	0.254
	Lignite Production	1.62×10^{-5}	0.015	0.196

Tab.4 Regression Results for CO Concentration Models

All three predictors remained statistically significant in the multiple regression model, with standardized coefficients indicating that nightlight intensity is the strongest predictor of CO concentrations, followed by electricity consumption and then lignite production.

3.5 Regional analysis

Regional analysis revealed significant spatial heterogeneity in the relationship between nightlight intensity and CO concentrations across Thailand. Table 5 summarizes the key findings for each region.

Region	Corr.	R^2	CO*	NL*	Regression Equation
Bangkok Metro	0.598	0.358	0.038	3.812	0.025 + 0.002·NL
Northern	0.548	0.300	0.034	0.461	0.023 + 0.024·NL
Northeastern	0.472	0.223	0.036	0.568	0.026 + 0.017·NL
Central	0.571	0.326	0.037	0.648	0.025 + 0.019·NL
Southern	0.334	0.112	0.032	1.163	0.026 + 0.005·NL

Tab.5 Regional Analysis of Nightlight-CO Relationship *CO Mean (mol/m^2), NL = Nightlight Mean (nanoWatts/sr/cm^2)

The regional analysis indicates that:

- The Bangkok Metropolitan Region shows both the highest CO levels (0.038381 mol/m^2) and by far the highest nightlight intensity (3.812006 nanoWatts/sr/cm^2), reflecting intense urbanization and associated pollution;

- The correlation between nightlight intensity and CO is strongest in the Bangkok Metro region (r = 0.598) and weakest in the Southern region (r = 0.334), suggesting that the relationship between urbanization and pollution varies by regional context;
- The slope of the regression line (coefficient for nightlight) varies significantly across regions, with the Northern region showing the steepest slope (0.024286), indicating that a unit increase in nightlight intensity is associated with a larger increase in CO concentrations in this region compared to others;
- The Southern region shows a relatively high nightlight intensity (1.162583 nanoWatts/sr/cm^2) but the lowest CO levels (0.031675 mol/m^2) and weakest correlation, suggesting that nightlight in this region may be associated with activities that produce less CO pollution, possibly related to tourism and coastal development.

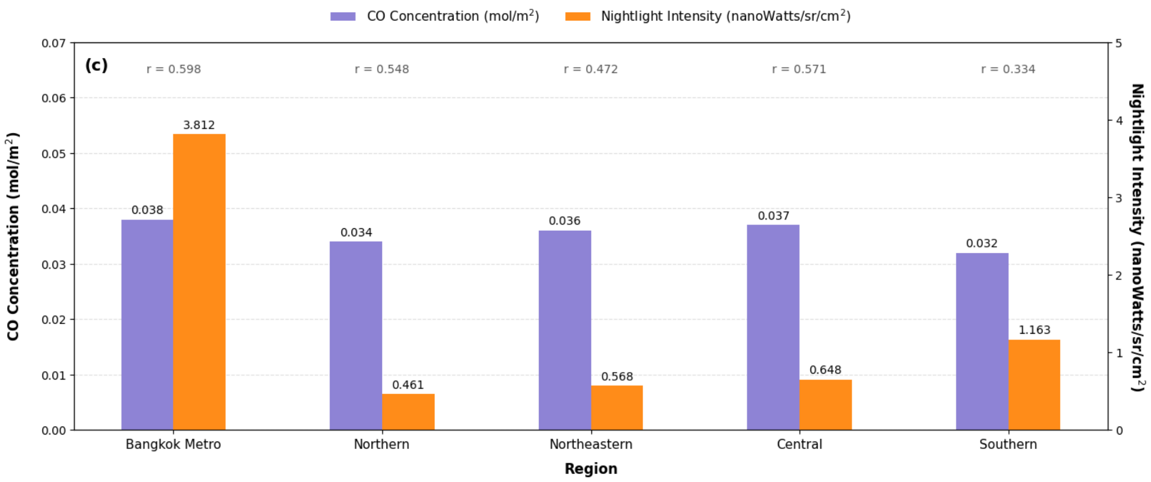

Fig.5 Regional comparison of CO concentrations and nightlight intensity across Thailand's five regions, averaged over 2019-2024

Fig.5 presents a regional comparison of mean CO Concentration and Nightlight Intensity in Thailand. Data labels above bars represent mean values; r values indicate the Pearson correlation coefficient between the two variables for each specific region.

3.6 Provincial analysis

The provincial analysis focused on key provinces representing different regions and levels of urbanization. Tab.6 presents the correlation coefficients and regression results for these provinces.

Province	Corr.	R^2	CO*	NL*	Region
Bangkok	0.547	0.299	0.039	5.025	Bangkok Metro
Samut Prakan	0.627	0.394	0.039	3.750	Bangkok Metro
Nonthaburi	0.486	0.236	0.038	3.523	Bangkok Metro
Pathum Thani	0.564	0.319	0.037	2.952	Bangkok Metro
Nakhon Ratchasima	0.501	0.251	0.035	0.530	Northeastern
Chiang Mai	0.491	0.241	0.035	0.422	Northern
Songkhla	0.195	0.038	0.030	0.844	Southern

Tab.6 Provincial Analysis of Nightlight-CO Relationship for Key Provinces *CO Mean (mol/m^2), NL = Nightlight Mean (nanoWatts/sr/cm^2)

The provincial analysis shows that:

- Bangkok has the highest nightlight intensity (5.024764 nanoWatts/sr/cm^2) among all provinces, followed by other provinces in the Bangkok Metropolitan Region;

- Samut Prakan shows the strongest correlation between nightlight and CO (r = 0.627), possibly due to its mix of industrial activities, residential areas, and transportation infrastructure;
- Songkhla in the Southern region shows a notably weak correlation (r = 0.195), confirming the regional pattern that nightlight intensity in the Southern region may be associated with activities that produce less CO pollution;
- The provinces in the Bangkok Metropolitan Region show similar CO levels despite varying nightlight intensities, suggesting potential saturation effects or differences in the types of urban activities and infrastructure generating nighttime light.

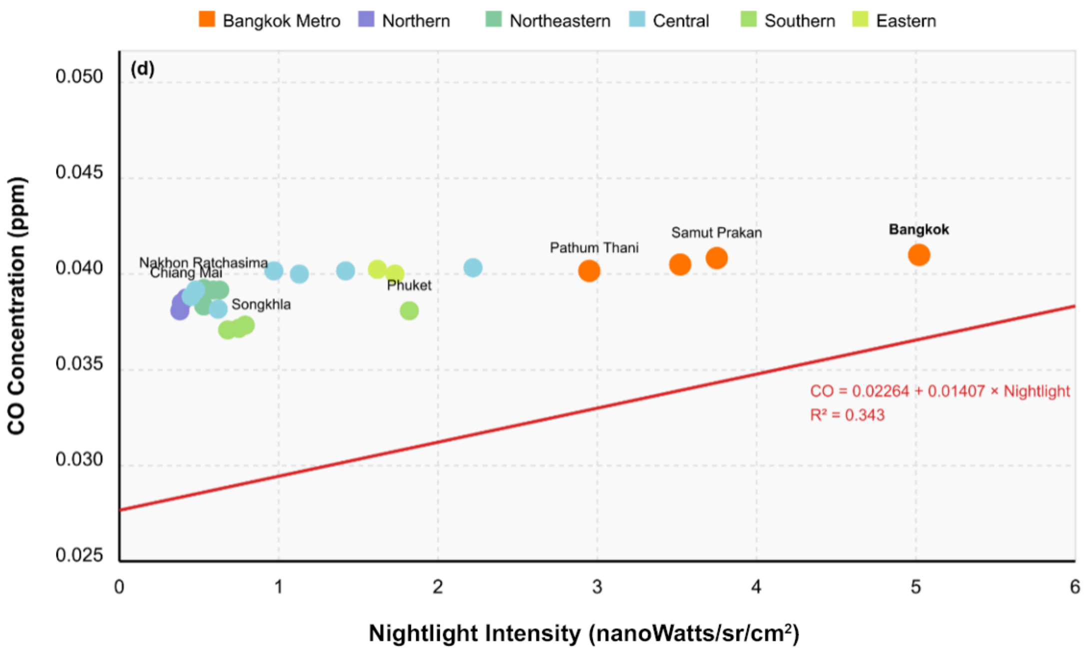

Fig.6 Scatter plot of CO concentrations versus nightlight intensity for all provinces in Thailand, with key provinces highlighted

Fig.6 presents a scatter plot of CO concentrations versus nightlight intensity for all provinces, highlighting the positive relationship between these variables and the position of key provinces. The red line represents the linear regression model.

3.7 Lag correlation analysis

Lag correlation analysis was performed to explore potential temporal relationships between nightlight intensity and CO concentrations. Tab.7 presents the correlation coefficients for different lag periods at the national level.

Lag (months)	Nightlight leading CO	CO leading Nightlight
0	0.5855	0.5855
1	0.3961	0.5029
2	0.1869	0.2056
3	-0.0587	-0.1037
4	-0.1689	-0.4125
5	-0.3237	-0.4514
6	-0.4926	-0.4989

Tab.7 Lag Correlation Analysis of Nightlight and CO Relationship

The lag correlation results indicate that:

- The strongest correlation between nightlight intensity and CO concentrations occurs at lag 0 (contemporaneous relationship), suggesting that the two variables generally change together;
- The correlation between lagged nightlight and current CO declines rapidly as the lag increases, becoming negative at lag 3, which suggests that nightlight changes do not strongly predict future CO changes beyond a month or two;
- The correlation between lagged CO and current nightlight also declines with increasing lag but remains stronger than in the opposite direction at lag 1, suggesting that CO changes might slightly lead nightlight changes in some contexts;
- The negative correlations at longer lags likely reflect the strong seasonal patterns in both variables, as periods of high values are followed by periods of low values approximately 6 months later.

This temporal analysis provides a more nuanced understanding of the relationship between urban development and pollution, suggesting that while they generally change together, there may be complex feedback mechanisms at work with slight temporal offsets.

4. Discussion

4.1 Interpreting the nightlight-pollution relationship

The strong positive correlation (r = 0.586) between nightlight intensity and CO concentrations confirms our primary hypothesis that nightlight data can serve as an effective proxy for monitoring urban-related pollution. This finding is consistent with the nature of carbon monoxide as a pollutant directly linked to combustion processes associated with human activities, particularly transportation and industrial operations.

However, the observed strength of this relationship is influenced by several factors, as discussed in the following subsections.

Seasonal variations

The differing seasonal patterns of the two variables suggest that while urbanization (nightlight intensity) contributes to pollution, meteorological and other factors also play significant roles in determining CO concentrations.

The stronger seasonal component in CO concentrations (26% of variation) compared to nightlight intensity (19% of variation) reflects these additional influences.

Thailand's distinct monsoon climate creates pronounced seasonal variations in both variables. The peak in CO concentrations during the dry season (January-April) likely reflects a combination of:

- Reduced atmospheric mixing and dispersion due to temperature inversions common during this period;
- Increased biomass burning in agricultural areas surrounding urban centers;
- Reduced rainfall that would otherwise remove pollutants from the atmosphere;
- Possible changes in transportation patterns associated with tourism and dry season activities.

The peak in nightlight intensity during December-April coincides with:

- Holiday periods (Christmas, New Year, Thai New Year), when decorative lighting increases;
- Peak tourist season when commercial activities intensify;
- Clearer atmospheric conditions that allow for better satellite detection of lights.

These different drivers of seasonality partially explain why the correlation between the two variables, while strong, is not stronger.

Understanding these seasonal patterns has important implications for interpreting the relationship between urban development and pollution, as well as for designing effective monitoring and mitigation strategies.

Energy consumption patterns

The multiple regression results indicate that energy usage—particularly electricity consumption and fossil fuel production—mediates the relationship between urban development and pollution.
The standardized coefficients from our multiple regression model (Tab.4) provide important insights into the relative importance of different factors:

- Nightlight intensity (Standardized coefficient = 0.498) remains the strongest predictor of CO concentrations, suggesting that urban development and human activity have direct effects on pollution beyond energy consumption;
- Electricity consumption (Standardized coefficient = 0.254) emerges as the second most important factor, reflecting the contribution of power generation to atmospheric CO, particularly from older plants with less efficient combustion systems;
- Lignite production (Standardized coefficient = 0.196), while statistically significant, has a smaller effect, potentially reflecting the gradual improvement in combustion efficiency and pollution control technologies in Thailand's power sector.

The finding that nightlight intensity remains significant even after controlling for energy consumption suggests that it captures aspects of urban development and human activity that affect pollution through mechanisms beyond stationary energy use, with transportation likely being the primary factor. This aligns with established knowledge that in most urban areas, particularly in developing economies, vehicle emissions represent the dominant source of carbon monoxide.

Spatial heterogeneity

The regional and provincial analyses reveal substantial spatial differences in both the levels of and the relationship between nightlight intensity and CO concentrations. These differences can be attributed to several factors:

- Varying urban forms and development patterns, particularly the contrast between the dense Bangkok Metropolitan Region and more dispersed provincial cities, may also contribute to these spatial differences.
- Different economic activities in each region may also contribute to these differences, with the Southern region's tourism economy potentially producing less CO per unit of nightlight than the industrial activities in the Central and Bangkok Metropolitan regions;
- Geographical factors, such as topography and meteorological conditions that affect pollutant dispersion, are particularly relevant in the mountainous Northern region;
- Different transportation systems and vehicle fleets, with older vehicles more common in some regions. Moreover, these spatial disparities highlight the importance of understanding accessibility and inclusivity in urban planning, as barriers to access can vary significantly across different urban forms (Cutini & Mara, 2025; Ercetin, 2024).

The strongest correlation in the Bangkok Metro region (r = 0.598) likely reflects the dominance of transportation as both a source of CO emissions and a driver of urban lighting, while the weaker correlation in the Southern region (r = 0.334) may indicate a decoupling between lighting and pollution sources in coastal tourist areas.

4.2 Public health implications

The demonstrated relationship between nightlight intensity and CO concentrations has important public health implications. Carbon monoxide is a toxic pollutant that binds to hemoglobin in the blood with an affinity approximately 250 times that of oxygen, forming carboxyhemoglobin (COHb) and reducing the oxygen-carrying capacity of blood (Raub et al., 2000). Even at the relatively low concentrations observed in this study

(Maximum monthly average of 0.051766 mol/m^2), chronic exposure may have subtle health effects, particularly for vulnerable populations such as those with cardiovascular disease, pregnant women, and young children.
Our findings support the use of nightlight data as a proxy indicator for potential CO exposure in urban areas, which could be particularly valuable for public health monitoring in areas where direct pollution measurements are limited. The seasonal and spatial patterns identified could inform targeted interventions during high-risk periods and in high-risk areas.
Moreover, the connection between urban development, as measured by nightlight intensity, and CO pollution underscores the importance of integrating public health considerations into urban planning and development policies. As Thailand continues to urbanize, strategies that mitigate the pollution impacts of development—such as improved transportation systems, cleaner energy technologies, and urban design that reduces traffic congestion—will be crucial for protecting public health.

4.3 Implications for environmental monitoring

Our study demonstrates that satellite-derived nightlight data can serve as a useful proxy for monitoring urban-related air pollution, particularly CO concentrations (Cauwels et al., 2014). This approach offers several advantages:

- Global coverage and consistency, allowing for monitoring in areas where ground-based measurements are sparse;
- High spatiotemporal resolution, enabling detailed analysis of patterns and trends;
- Cost-effectiveness compared to establishing and maintaining extensive ground-based monitoring networks;
- Ability to observe rapid urban development and associated environmental impacts in near-real time.

However, our results also highlight the limitations of using nightlight data alone for pollution monitoring:

- Moderate R^2 value (0.343) in the simple regression model indicates that nightlight intensity explains only about one-third of the variation in CO concentrations;
- Substantial regional and seasonal variations in the relationship suggest that calibration factors would need to be developed for different contexts;
- The influence of energy-related factors indicates that complementary data sources should be integrated for more accurate pollution estimation.

A hybrid approach that combines satellite-derived nightlight data with other remotely sensed parameters (such as land use, vegetation indices, and meteorological data) and limited ground-based measurements could provide a more robust framework for urban pollution monitoring in rapidly developing regions.

4.4 Comparison with previous studies

Our findings both support and extend previous research on the relationship between nightlight data and air pollution indicators. The positive correlation we observed between nightlight intensity and CO concentrations in Thailand aligns with the findings of (Wang et al., 2019), who demonstrated the utility of VIIRS data in predicting various air pollutants, including CO, in urban environments.
Our methodological approach is similar to that of (Zuo et al., 2022), who investigated the correlation between Carbon dioxide concentrations and nightlight intensity using integrated DMSP - OLS and NPP - VIIRS data. While their study focused on China and found varying relationships between nightlight data and carbon metrics due to different urban industrial structures across regions, our work in Thailand reveals similar spatial heterogeneity in the nightlight-pollution relationship. Their findings reinforce the importance of considering regional industrial development patterns when interpreting remote sensing data correlations (Zhuo et al., 2009).

The relationship between nightlight intensity as a proxy for economic activity and environmental impacts is further supported by (Chen & Nordhaus, 2011), who validated the use of luminosity data for estimating socioeconomic statistics across different regional contexts. Similarly, developed methodologies for creating harmonized nightlight datasets (Li et al., 2020) that improve the reliability of such data for long-term environmental monitoring applications.

The observed seasonal patterns in CO concentrations are consistent with previous Thailand-specific research by (Pochanart et al., 2003), who identified significant seasonal variations in Bangkok's air quality linked to both meteorological conditions and changes in emission patterns. Our finding that CO peaks during the dry season (January-April) aligns with their results and extends the analysis to a national scale over a more recent time period.

The regional and provincial analysis extends the work of (Patarasuk et al., 2016), who investigated the carbon footprint of Thailand's urban centers using a combination of remote sensing and ground-based measurements, by providing a more detailed understanding of the spatial patterns and drivers of CO pollution across the country.

4.5 Policy implications

Our findings have several implications for urban development, environmental management, and public health policies in Thailand:

- Integrated Planning: The strong relationship between nightlight intensity and CO concentrations suggests that urban development and air quality management should be addressed in an integrated manner. Policies aimed at sustainable urban development should explicitly consider potential impacts on air quality and public health;
- Seasonal Targeting: The pronounced seasonal patterns in CO concentrations indicate that pollution control measures should be intensified during the dry season (January-April), particularly in regions prone to elevated pollution levels;
- Energy Transition: The influence of lignite production and electricity consumption on CO levels supports Thailand's ongoing energy transition toward cleaner sources. Accelerating this transition, particularly in the power sector, could help mitigate the pollution impacts of continued urbanization. Furthermore, adopting sustainable logistics and optimizing urban transport through new technological methods is essential for reducing the environmental footprint of growing cities (Oguz & Tanyas, 2024; Valentini et al., 2023);
- Regional Differentiation: The significant spatial heterogeneity in the nightlight-CO relationship suggests that a one-size-fits-all approach to urban environmental management may be ineffective. Policies should be tailored to the specific characteristics and challenges of each region, with particular attention to the Bangkok Metropolitan Region, where both nightlight intensity and CO levels are highest;
- Monitoring Enhancement: The utility of nightlight data for pollution monitoring suggests that integrating satellite-derived indicators into Thailand's environmental monitoring framework could enhance coverage and cost-effectiveness, particularly for rapidly developing areas where ground-based monitoring is limited.

Implementing these policy recommendations would require coordination across multiple government agencies, including those responsible for urban planning, transportation, energy, environment, and public health, as well as engagement with local communities and the private sector.

4.6 Limitations and future research

While this study provides valuable insights into the relationship between urban development and pollution in Thailand, several limitations should be acknowledged:

Spatial resolution

The provincial-level analysis may obscure important local variations within provinces. Future research could employ higher spatial resolution data to examine city-level or sub-district patterns, potentially revealing different relationships in urban cores compared to suburban or peri-urban areas.

Applying the same methodological approach at different spatial scales could also help identify scale-dependent effects and determine the optimal resolution for monitoring the urbanization-pollution relationship.

Additional pollutants

This study focused exclusively on CO concentrations as a measure of pollution. Future research could incorporate additional pollutants such as Particulate Matter (PM2.5, PM10), Nitrogen Oxides (NO_x), and Volatile Organic Compounds (VOCs) to develop a more comprehensive understanding of urban environmental impacts. The relationship between nightlight intensity and these other pollutants may differ from what we observed for CO, potentially revealing more complex patterns of urban environmental quality. Furthermore, analyzing multiple pollutants simultaneously could help identify common sources and inform more integrated control strategies.

Socioeconomic factors

While nightlight intensity serves as a proxy for urban development, incorporating additional socioeconomic indicators such as GDP, population density, and transportation statistics could provide more nuanced insights into the drivers of pollution.

Future research could develop more comprehensive models that include these socioeconomic variables, potentially increasing explanatory power and identifying specific aspects of development that contribute most significantly to CO pollution (Hu et al., 2017).

Long-term trends and climate change

Our six-year study period provides insights into recent patterns but may not capture longer-term trends or the potential impacts of climate change on the relationship between urban development and air pollution (Longato et al., 2025). Extended time series analysis over multiple decades could help identify how this relationship has evolved and might continue to evolve in response to changing climate conditions and urban development patterns. As Pennino (2024) emphasizes, global warming poses increasing risks to urban territories, necessitating that environmental monitoring frameworks evolve to support not just pollution mitigation, but also specific adaptation practices for challenges like extreme heat.

5. Conclusions

This study has demonstrated a strong positive correlation between nightlight intensity and carbon monoxide concentrations in Thailand, suggesting that satellite-derived nightlight data can serve as an effective proxy for monitoring urban-related pollution. The relationship is moderated by seasonal patterns, energy consumption behaviors, and spatial factors, with significant variations across regions and provinces.

The multiple regression results indicate that while nightlight intensity remains the strongest predictor of CO concentrations, energy-related factors provide significant additional explanatory power. This suggests that while the correlation between urban activity and pollution is strong, the actual causal mechanisms are complex and mediated by energy systems and consumption patterns.

Regional and provincial analyses reveal substantial spatial heterogeneity, with the Bangkok Metropolitan Region showing both the highest nightlight intensity and CO levels, and the strongest correlation between these variables. This spatial differentiation highlights the importance of context-specific approaches to urban environmental management.

The lag correlation analysis indicates that the strongest relationship between nightlight intensity and CO concentrations occurs contemporaneously, suggesting that these variables generally change together. However, there is some evidence that changes in CO concentrations might slightly lead to changes in nightlight intensity in certain contexts, pointing to potential feedback mechanisms between environmental conditions and urban activity patterns.

Given the public health significance of CO as a toxic pollutant, our findings have direct relevance for environmental management and public health protection in Thailand. The demonstrated relationship between nightlight intensity and CO concentrations provides a foundation for more targeted and effective pollution monitoring strategies.

As Thailand continues its path of economic development and urbanization, understanding these complex relationships between urban development, energy consumption, and environmental conditions will be crucial for balancing growth objectives with environmental sustainability and public health protection. Future research should focus on higher-resolution spatial analysis, incorporation of additional pollutants, source attribution, and detailed investigation of the mechanisms linking urban development patterns to environmental outcomes.

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Image Sources

All the figures have been elaborated by the authors.

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