Space–Time Analysis of Nighttime Light Intensity in Phoenix, Arizona (1992–2024)

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Abstract

This paper analyzes nighttime light (NTL) intensity in Phoenix, Arizona from 1992 to 2024 using harmonized DMSP-OLS (Defense Meteorological Satellite Program Operational Linescan System) and VIIRS (Visible Infrared Imaging Radiometer Suite) datasets. By integrating a space–time cube with Emerging Hot Spot Analysis, the study identifies persistent, intensifying, and emerging patterns of urban growth. The results show sustained expansion of the urban core alongside rapid suburban development. The findings demonstrate that NTL data provide an effective proxy for urbanization and highlight the value of space–time analysis for understanding long-term urban dynamics. The methodology is transferable and can be applied to other cities worldwide for monitoring urban growth and spatial development.

1. Introduction

Urbanization is one of the most significant global processes of the 21st century, shaping land use, infrastructure, and energy consumption (Burger et al., 2019, p. 1). Satellite-derived nighttime light (NTL) data provide a valuable proxy for human activity, allowing researchers to observe urbanization patterns from space (Pei et al., 2025). Unlike environmental indicators such as air pollution, NTL data directly capture artificial illumination associated with built infrastructure and socioeconomic activity (Singh et al., 2023, p. 2121).

Previous studies have demonstrated the usefulness of NTL data for monitoring urban expansion and economic development (Small & Elvidge, 2012; Zhang et al., 2016). However, long-term analysis requires harmonization between datasets due to differences in sensor characteristics between Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS) and Visible Infrared Imaging Radiometer Suite (VIIRS) data (Elvidge et al., 2013).

Phoenix, Arizona, provides an ideal case study due to its rapid population growth and expansion into surrounding desert landscapes. This study builds on prior work by integrating harmonized NTL datasets with space–time pattern mining techniques to evaluate both spatial and temporal dynamics of urbanization. Figure 1 illustrates the spatial extent of Phoenix, Arizona, encompassing its metropolitan area and highlighting key geographical features that influence its urban development trajectory. Specifically, the arid environment and mountainous terrain have constrained and directed urban growth, leading to distinct patterns of NTL intensity (Tan et al, 2025).

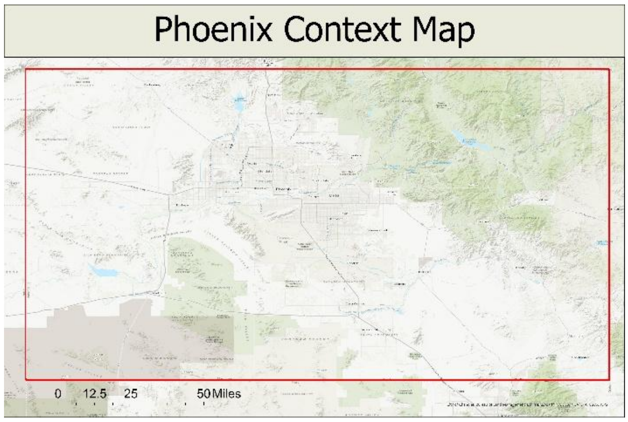

Figure 1. Phoenix Context Area

2. Methods

2.1 Data Sources

This study used harmonized global nighttime light data from the GEE Humanitarian Nighttime Lights (HNTL) dataset, which integrates DMSP-OLS (1992–2013) and VIIRS (2014–2024) observations into a consistent time series. Annual composites were clipped to the Phoenix metropolitan area (Maricopa County) using administrative boundaries obtained from Esri’s Living Atlas. The data span from 1992 to 2024, allowing for a comprehensive spatiotemporal analysis of urban dynamics (Zhao et al., 2022). The integration of these diverse datasets on platforms like Google Earth Engine facilitates efficient processing and analysis of extensive spatiotemporal data for urban expansion and energy consumption studies (Anucharn et al., 2025). This approach enables the quantitative characterization of socioeconomic activity intensity and urbanization processes over extended periods (Li et al., 2020, p. 1). Specifically, the harmonized NTL dataset, known for its temporal consistency and enhanced sensitivity, allows for a more accurate assessment of urban growth and economic development, particularly in quantifying subnational activities and extending historical coverage (Jhamb et al., 2025). These data products offer monthly and annual temporal resolutions, which are crucial for detailed analyses of socioeconomic activities and construction policies within urbanized regions (Xin et al., 2017).

2.2 Data Processing

Data processing was conducted in ArcGIS Pro and included the following steps:

1. Raster clipping to the study extent for each year (1992–2024)
2. Creation of a mosaic dataset with temporal attributes
3. Conversion to a multidimensional raster dataset
4. Construction of a space–time cube using annual aggregation
5. Visualization using 2D maps, temporal profiles, and 3D representations
6. Application of Emerging Hot Spot Analysis

This robust methodological framework enables the identification of statistically significant spatiotemporal clusters of high and low NTL intensity, thereby revealing the dynamic evolution of urban development and its associated socioeconomic activities (Katsuyuki, 2025). The DMSP/OLS nighttime light data, with a 1x1 km grid spatial resolution and brightness values from 0–63, further provides insights into the economic level of the study area, while LandScan population grid data from ORNL complements this by illustrating population distribution (Chen et al., 2021, p. 5). To maintain consistency across disparate NTL datasets, researchers often employ critical calibration steps to mitigate issues arising from sensor discrepancies and saturation, thereby ensuring reliable trend analysis over extended periods (Ruan & Zou, 2019, p. 71; Shang et al., 2021, p. 4). For example, researchers have employed invariant region methods to calibrate DMSP/OLS data, enhancing its utility for estimating electricity consumption, although without incorporating broader socioeconomic factors (Swardika & Santiary, 2023, p. 167). Addressing these limitations, a global annual simulated VIIRS NTL dataset, generated through a U-Net super-resolution network for cross-sensor calibration, provides a continuous and consistent 500-meter resolution from 1992 to 2024, offering substantial improvements for long-term urban research (Chen et al., 2024; Sun et al., 2025, p. 3).

2.3 Analytical Approach

Nighttime light intensity is used as a proxy for urbanization, reflecting built infrastructure, population activity, and energy consumption (Lu & Coops, 2018, p. 1). However, this proxy has limitations, as radiance values may also capture non-residential lighting and variations in lighting technology (Levin et al., 2019, p. 111497; Nachtlichter et al., 2024, p. 11).

To move beyond a purely pixel-based analysis, this study employs a space–time cube combined with Emerging Hot Spot Analysis. This approach enables the identification of statistically significant clusters and trends over time, capturing not only where urbanization occurs but how it evolves spatially and temporally.

This involves classifying spatiotemporal bins into distinct categories such as new, intensifying, persistent, sporadic, or diminishing hotspots, offering a more nuanced understanding of urban cluster life cycles than static maps alone (Baeza-González & Kamakura, 2025, p. 5; Jing et al., 2021, p. 1775). This method provides robust statistical evidence for detecting areas of sustained growth or decline, distinguishing them from transient fluctuations (Baeza-González & Kamakura, 2025, p. 11; Cooke et al., 2019, p. 206). The ability to differentiate between these temporal patterns allows for a more accurate assessment of urban dynamics and facilitates targeted policy interventions(Jing et al., 2021, p. 1779; Pulselli et al., 2008, p. 131). Furthermore, analyzing these spatiotemporal clusters in conjunction with demographic and economic data can unveil the underlying drivers of urban expansion and contraction, offering a comprehensive perspective on urban systems (Liang et al., 2026; Singh et al., 2023, p. 1562).

3. Results

3.1 Temporal Trends

Results show a steady increase in mean annual nighttime light intensity across Phoenix from approximately 8.7 DN in 1992 to 15.6 DN in 2024. This upward trend reflects sustained population growth and increasing urban development; post-2010 values consistently exceeded the long-term mean.

This aligns with broader regional trends observed in other rapidly urbanizing areas, where NTL data serves as a reliable indicator of increased anthropogenic activity and infrastructure development (Li et al., 2020, p. 7). For instance, studies in the Loess Plateau demonstrate that urban areas have tripled over three decades, as evidenced by spatiotemporal evolution features captured by nighttime light images (Chen et al., 2023). Similarly, analyses in megaregions like Chengdu-Chongqing reveal peri-urban brightening, often exceeding historic core radiance by 40%, indicating significant luminous sprawl despite population declines (Liang et al., 2026). This phenomenon underscores the utility of NTL data in discerning nuanced patterns of urban expansion and economic transformation beyond simple population counts. Figure 2 shows the mean annual NTL intensity values for the Phoenix metropolitan area in 2D from 1992 to 2024, graphically illustrating the consistent upward trajectory in urban luminescence. The observed increase in NTL intensity directly correlates with the expansion of built-up areas and the densification of existing urban fabrics, particularly evident in the rapid growth along major transportation corridors and the conversion of agricultural land into urbanized regions (Kuyela & Lu, 2025).

Figure 3 shows these values in 3D. This three-dimensional representation further highlights the volumetric growth of the urban area, illustrating not only horizontal expansion but also potential vertical intensification within established zones (Zhao et al., 2020, p. 103882).

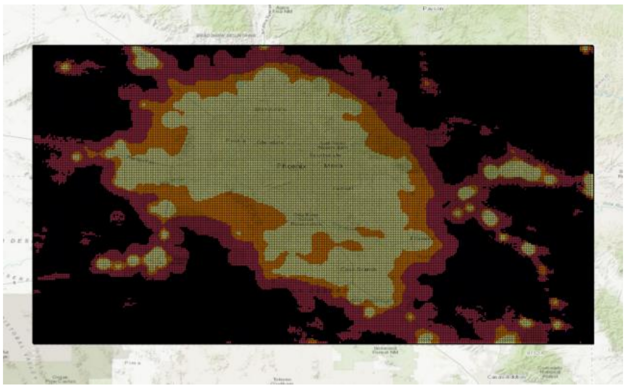

Figure 2. 2D Visual of Intensity Values

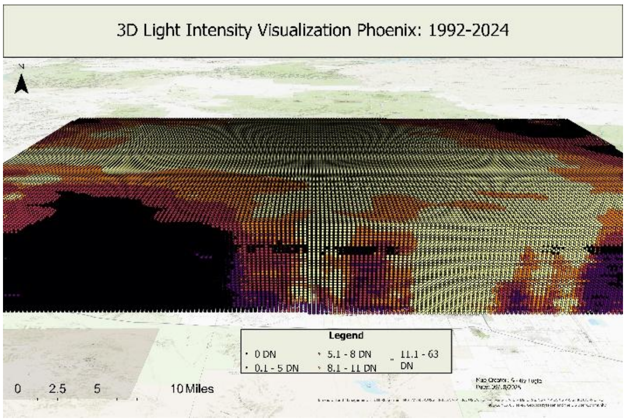

Figure 3. 3D sliced view of downtown Phoenix.

3.2 Spatial Patterns

Spatial analysis reveals a clear distinction between urban cores, suburban areas, and desert peripheries. High-intensity values (>12 DN) are concentrated in central Phoenix, Mesa, and Tempe, while moderate values characterize suburban regions. Surrounding desert areas remain consistently dark, indicating limited development.

This spatial differentiation highlights the heterogeneous nature of urban growth, often characterized by distinct land-use patterns and varying levels of anthropogenic influence. This aligns with findings in other urban systems where dense population centers exhibit higher nighttime light intensity, while peripheral areas show lower values, suggesting a correlation between NTL and population density (Tan et al, 2025). The observed differentiation further emphasizes the utility of NTL data in distinguishing between core urban, peri-urban, and rural areas, reflecting the gradual conversion of rural pixels into peri-urban and subsequently into core urban regions (Singh et al., 2023, p. 1567).

The intensity values in these highly illuminated areas demonstrate significant positive trends, indicative of sustained outward growth from urban cores and an increasing spatial extent of urban entities (Withanage & Shen, 2024, p. 353). This outward expansion often manifests as a decline in dark areas and an increase in illuminated areas, particularly evident in the rapid conversion of undeveloped land at the urban fringe (Lu & Coops, 2018, p. 5).

3.3 Space–Time Patterns

The Emerging Hot Spot Analysis tool in ArcGIS Pro classifies statistically significant clusters of high or low values over time into categories such as persistent, intensifying, diminishing, and emerging hot or cold spots.

These categories, as defined by Esri (Li et al., 2023, p. 4) in this study help explain long-term nighttime light intensity patterns across the Phoenix metropolitan area.

● Persistent Hot Spot – A location that has been a statistically significant hot spot for at least 90 percent of the time-step intervals, with no significant upward or downward trend in intensity. This category includes central Phoenix and Mesa, where nighttime light values remained consistently high throughout the 1992–2024 period, reflecting long-standing urban cores and dense infrastructure (Chang et al., 2025).

● Intensifying Hot Spot – A location that has been a statistically significant hot spot for at least 90% of the time-step intervals, including the final year, and shows a statistically significant upward trend in clustering intensity (Li et al., 2023, p. 4; Rahaman et al., 2024, p. 7). In this study, intensification of hot spots is evident in areas such as Tempe and Glendale, where existing urban development has become denser over time, reflecting increased urban density and economic activity.

● Emerging Hot Spot – A location that became a statistically significant hot spot more recently in the time series. In Phoenix, suburban municipalities such as Chandler, Gilbert, and Surprise fit this category, highlighting rapid population growth (García-Vázquez, 2019, p. 240) and housing development during the 2000s and 2010s (Pfeiffer et al., 2019, p. 1642). These areas represent the outward expansion of the metropolitan area into previously undeveloped desert land.

● Persistent Cold Spot – A location that has been a statistically significant cold spot for at least 90% of the time steps, with no substantial change in intensity. In Phoenix, this pattern is found in the surrounding desert areas beyond the metropolitan fringe, where light intensity remains consistently low, marking the contrast between the sprawling urban footprint and the rural desert environment.

These categories not only clarify where Phoenix has experienced sustained urban brightness but also whether these conditions are long-standing, intensifying, or newly emerging. This interpretation is crucial for urban planning and sustainability, as persistent and intensifying hotspots indicate areas of ongoing growth and energy consumption (Buchori et al., 2018, p. 190; Xu et al., 2019, p. 1). In contrast, emerging hotspots reveal the expansion of suburban development (Acheampong et al., 2016, p. 837; Gui et al., 2024). Persistent cold spots mark the boundaries of urbanization (Gupta, 2024, p. 145), underscoring the stark contrast between the illuminated city and the dark desert. These findings have direct implications for future urban development and resource allocation.

Further analysis of nighttime light intensity within specific local climate zones reveals distinct patterns of urban development and energy expenditure, with densely built-up areas consistently exhibiting the highest radiance values (Geletič et al., 2025). This observation supports the understanding that artificial lighting, a key component of nighttime radiance, is directly correlated with anthropogenic activity and urban infrastructure density (Liu et al., 2025). Conversely, regions characterized by lower radiance values frequently correspond to less developed or natural landscapes, thereby underscoring the utility of NTL data in delineating the urban-rural interface and quantifying developmental gradients (Brazel et al., 2007, p. 176; Paliza et al., 2026; Small & Elvidge, 2011).

Figure 4 presents the 3D hotspot, and this three-dimensional representation integrates spatiotemporal hot and cold spot analysis with topographic features, providing a comprehensive visualization of urban growth patterns and their associated environmental impact (Jing et al., 2021, p. 1777).

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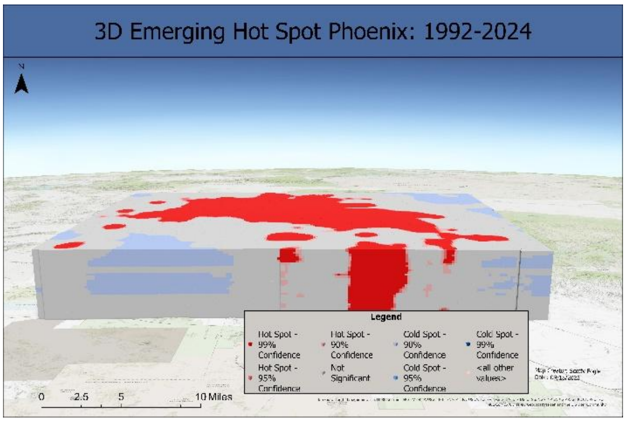

Figure 4. 3D Hotspot of Phoenix

4. Discussion

The findings demonstrate that urbanization in Phoenix is both persistent and expanding. Central urban areas have maintained high levels of nighttime illumination for decades, while suburban regions have transitioned into new and intensifying hotspots. These patterns align with demographic trends showing rapid population growth and suburban expansion (Kane et al., 2013). Figure 1 shows the trend for this as going up.

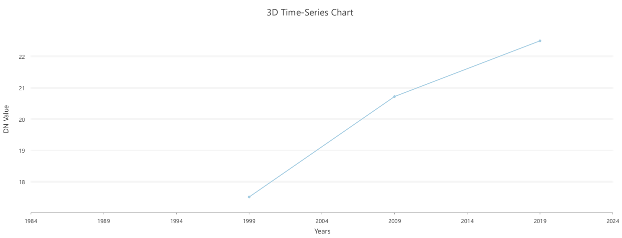

Figure 5. Chart of DN Values for Phoenix

The integration of space-time analysis provides a more comprehensive understanding of urban dynamics compared to static mapping. While traditional maps show where urbanization occurs, the space-time cube reveals whether changes are stable, emerging, or intensifying.

From an applied perspective, the results have important implications for urban planning, infrastructure development, and energy management. Persistent and intensifying hotspots indicate areas of continued development pressure, while emerging hotspots highlight regions of future growth. The methodology is highly transferable due to the global availability of harmonized NTL datasets (Li et al., 2020) and standard GIS tools.

This transferability allows for comparative urban studies across diverse geographical contexts, enabling the identification of universal urbanization patterns and region-specific anomalies (Chang et al., 2025). For example, this framework has been successfully applied to monitor spatio-temporal trajectories of urban area hotspots in Wuhan, China, and to evaluate urban expansion using land cover with nighttime lights (Ruan & Zou, 2019, p. 75; Singh et al., 2023, p. 1561). Moreover, research in the Chengdu-Chongqing megaregion and Bandung metropolitan area has similarly leveraged nighttime light data to identify peri-urban brightening, population decoupling, and the emergence of new economic centers, further validating the broad applicability of this analytical approach (Liang et al., 2026; Sakti et al., 2024, p. 7). Furthermore, such evidence-based inference and quantification of urban expansion using high-resolution satellite imagery and advanced detection algorithms, such as YOLOv8, combined with GIS-integrated analysis, enhance the applicability of model outputs by providing precise, time-stamped spatial data to support infrastructure planning and land-use regulation in rapidly growing regions (Pahuja et al., 2025, p. 26630). These robust methodologies allow for the identification of specific areas requiring interventions such as improved infrastructure or targeted development initiatives, thereby enhancing the efficacy of urban planning and resource allocation strategies (Zhong et al., 2023).

5. Limitations

Although nighttime light data provide a useful proxy for urbanization, they do not perfectly represent population density or land use (Chuanbao et al., 2025). Variations in lighting technology, energy efficiency, and non-residential illumination can influence radiance values (Levin et al., 2019, p. 111508). Additionally, despite harmonization efforts, differences between DMSP-OLS and VIIRS sensors may introduce residual inconsistencies (Chen et al., 2020, p. 3). These limitations should be considered when interpreting long-term trends.

Furthermore, while current methodologies effectively delineate urban expansion, the integration of multispectral or hyperspectral data could provide richer insights into urbanization dynamics and their environmental impacts, addressing challenges in sustainability, resilience, and equity (Pahuja et al., 2025, p. 26631). Future research could also incorporate socioeconomic and demographic data to better understand the drivers and consequences of urban growth, moving beyond purely physical indicators to address the complexities of urban-rural economic disparities (Zhai et al., 2025). Moreover, the increasing resolution of nighttime lights data promises to enable the identification of finer-grained socioeconomic patterns within urban hubs, allowing for more nuanced urban planning and targeted interventions(Singh et al., 2023). The NDUI+ dataset, for example, offers enhanced granularity for detecting small-scale urban features, which is particularly valuable for precise urban climate zone studies and street-level urban heat island modeling(Singh et al., 2023). Future work can further benefit from integrating higher-resolution satellite imagery, systematic ground-truth validation, and advanced machine-learning models to improve prediction accuracy and address existing data limitations (Aybar et al, 2026). Specifically, advancements in satellite technology, such as the Jilin-1 constellation, offer significantly higher spatial resolutions (e.g., 130m compared to 500m for VNP46A2), which could provide more detailed and accurate insights into urban land use and socioeconomic indicators(Debnath et al., 2025). This increased granularity facilitates the differentiation of unit values of NTL based on varying socioeconomic statuses, and allows for the application of advanced image processing techniques to mitigate the influence of industrial plants on light brightness differentiation (Debnath et al., 2025, p. 15; Withanage & Shen, 2024, p. 366).

6. Conclusions

This study applied space–time analysis to harmonized nighttime light data for Phoenix, Arizona, from 1992 to 2024. The findings confirm rapid, sustained urban expansion:

New hotspots emerged in suburban communities such as Chandler, Gilbert, and Surprise.

Overall, the results highlight Phoenix as a case of intensifying light pollution and urban growth, visible in both spatial distribution and temporal trends. Beyond Phoenix, the study demonstrates the value of nighttime lights as a proxy for urbanization and socioeconomic activity. Future research could compare NTL patterns with land cover change datasets (e.g., NLCD) to quantify the relationship between light expansion and urban sprawl.

Further research could focus on understanding the underlying causes of variations in NTL data and the impact of angular effects on observations, especially when light sources are not symmetrically distributed (Tan et al., 2021, p. 112883; Zheng et al., 2023). Additionally, the ongoing development of harmonized NTL datasets provides a continuous time series that will facilitate more consistent longitudinal analyses, particularly for bridging data discrepancies between DMSP and VIIRS sensors (Jhamb et al., 2025). This continuous data stream will be crucial for refining methodologies that address issues such as interannual inconsistencies, saturation effects, and blooming effects, which commonly plague NTL data (Pandey et al., 2013). Future studies could integrate more sophisticated methodologies like geographical and time-weighted regression to simultaneously capture the spatio-temporal non-stationarity inherent in urban development (Zhou et al., 2025, p. 15). This would allow for a more robust analysis of regional inequality dynamics by using multiple inequality measures to confirm observed trends (Patnaik & Mendez, 2024, p. 103). Moreover, a comprehensive validation study comparing satellite-based estimates of artificial light at night with individual-level measures is warranted to assess how population attributes might influence the validity of these satellite-derived metrics in public health research (Xiao et al., 2023, p. 115879). Such large-scale validation studies would enhance the utility of NTL data for monitoring evolving disparities in artificial light at night exposure across different socioeconomic and racial/ethnic groups, providing crucial evidence for targeted policy development aimed at ameliorating negative societal impacts (Xiao et al., 2023a, p. 10, 2023b). Additionally, research should investigate the measurement uncertainties induced by contextual settings across different geographic areas, which could inform more precise assessments of environmental injustice related to outdoor artificial light at night exposure (Liu & Kwan, 2024, p. 16). Furthermore, exploring the integration of additional modalities, such as Synthetic Aperture Radar and social media data, holds promise for enhancing NTL reconstruction by capturing nuanced aspects related to terrain and socioeconomic factors, thereby deepening insights into urban-rural economic dynamics (Zhai et al., 2025; Zhang et al., 2024, p. 7). Considering that NTL is recognized as a reliable proxy for measuring the scope and intensity of human activity, future research could leverage new finer-resolution NTL data from sensors like SDGSAT-1 and combine it with refined building density datasets, such as GHS-BUILT from Sentinel-2, to uncover new spatial patterns of population distribution and socioeconomic disparities, particularly in developing countries (Chen et al., 2024; Ehrlich et al., 2024, p. 50).

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