Illuminating Inequality: Spatial Patterns of Light Pollution and Socioeconomic Disparity Across England

Margaux Elijah Neri[1] and Vicente Tang[1]

[1] NOVA Information Management School (NOVA IMS), Universidade Nova de Lisboa, Campus de Campolide, 1070-312 Lisboa, Portugal

Correspondence: Margaux Elijah Neri (20240765@novaims.unl.pt)

Abstract. Artificial light pollution at night (ALAN) poses significant environmental and social challenges, impacting biodiversity, human health, and energy efficiency. This study examines the spatial distribution of ALAN across England and its relationship with population density, income, and Index of Multiple Deprivation (IMD). Using 2022 VIIRS data, Moran's I, Ordinary Least Squares (OLS), and Geographically Weighted Regression (GWR) were applied to assess these relationships. GWR outperformed OLS, capturing spatial heterogeneity and revealing localized associations. Population density emerged as the strongest predictor, particularly in urban areas, while income was a key factor in affluent southern regions. Elevated ALAN in deprived areas suggest the influence of additional factors like land use and infrastructure. These findings underscore the need for localized lighting strategies to address environmental and social disparities and promote sustainable urban planning.

Submission Type. Analysis

BoK Concepts. [AM7] Spatial statistics, [GS2] Economic aspects

Keywords. light pollution, inequality, England, spatial statistics

1 Introduction

Light pollution is a growing global concern, impacting human health (Kyba et al., 2015), biodiversity (Hölker et al., 2010), and energy efficiency (Linares Arroyo et al., 2024)~~.~~ Beyond the environmental challenges, it also reflects socioeconomic inequalities, as lower-income neighborhoods are often exposed to more intense artificial lighting due to outdated infrastructure (Xiao et al., 2023). England's diverse urban and rural landscapes offer a valuable context to explore these disparities and their spatial patterns.

This study investigates the spatial distribution of ALAN across England and its relationships with population density, income, and IMD deciles. Here, ALAN is defined as all anthropogenic light sources that illuminate the night sky based on satellite-detected radiance. Using spatial statistics, this paper seeks to answer: How is artificial nightlight distributed across England, and to what extent does it correlate with socioeconomic factors? The findings aim to contribute to sustainable urban planning and equitable lighting management strategies.

2 Methods

2.1 Data and Software Availability

The radiance data used was the 2022 VIIRS V2.2 median radiance composite, provided by the Earth Observation Group (EOG)[1]. Population density data was obtained from the 2021 Census TS001 dataset[2]. Income data for 2021 was sourced from the UK Office for National Statistics[3], while the 2019 IMD dataset was sourced from the UK Ministry of Housing, Communities & Local

[1] Earth Observation Group (EOG), VIIRS V2.2 median radiance composite, available at: https://eogdata.mines.edu/products/vnl/. Open-access.

[2] 2021 Census TS001 dataset, NOMIS, available at: https://www.nomisweb.co.uk/. Open-access,

[3] UK Office for National Statistics, 2021 income data, available at: https://www.ons.gov.uk/. Open-access.

Government[4]. All spatial data analyses were conducted using ArcGIS Pro 3.3. No code was collected, developed, or used in this work.

2.3 Spatial and Statistical Analysis

Radiance and socioeconomic data were aggregated by mean and standard deviation at the local authority level, then z-normalized for comparability. Spatial patterns of ALAN were analysed using Moran's I for clustering, OLS regression for global relationships, and GWR models for localized insights into spatial heterogeneity.

3 Results and Discussion

3.1 Spatial Patterns of Radiance

The baseline maps (Figure 1) reveal distinct spatial patterns of mean radiance and variability. Urban centres exhibit the highest levels of radiance and variability, reflecting dense infrastructure and population. Conversely, rural areas exhibit more homogeneous lighting conditions.

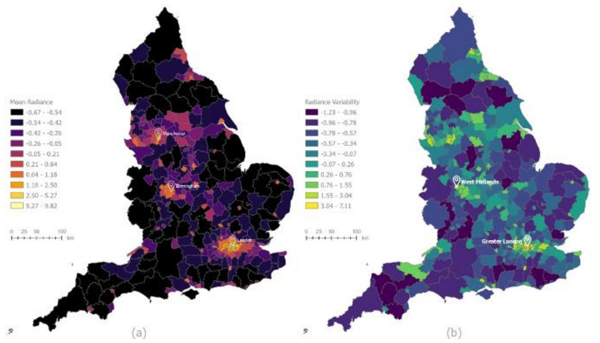

Figure 1. Baseline maps of (a) mean radiance and (b) radiance variability.

3.2 Socioeconomic Disparities in Radiance

Figure 2 highlights ALAN concentrations in the southeast, particularly in major cities like London, Birmingham, and Manchester, which align with areas of high population density. In regions such as Greater London and the West Midlands, radiance varies more sharply, while rural areas display lower and more uniform levels.

Higher income levels are mostly concentrated in the southeast, whereas deprivation is more common in the north. Within Greater London, there is a clear contrast in IMD, with clusters of disadvantage observed ndaf affluent boroughs.

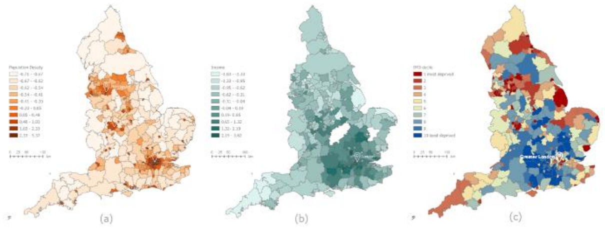

Figure 2. Baseline maps of (a) population density, (b)income, and (c) IMD.

3.3 Spatial Autocorrelation and Regression Analysis

Moran's I reveals significant positive spatial autocorrelation across all variables, indicating non-random clustering of radiance (Figure 3) and socioeconomic indicators (Figure 4) and highlighting the need for regression models to capture overall trends and local variability.

OLS using both population density and income produced a low corrected Akaike Information Criterion (AICc) of 82.73, outperforming models with single predictors (e.g., population density only: AICc = 542.87). Despite a high R^2 (0.89), residual analysis revealed spatial heterogeneity, especially in urban areas, suggesting the need for localized models. In contrast, income and IMD models showed limited ability to capture spatial variations.

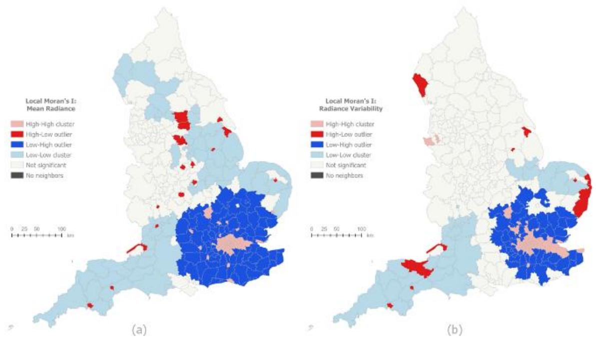

Figure 3. Clusters for (a) mean radiance and (b) radiance variability.

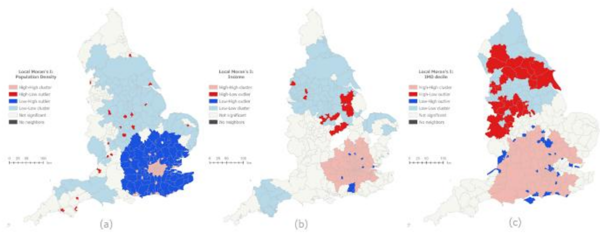

Figure 4. Clusters for (a) population density, (b) income, and (c) IMD.

GWR addressed this heterogeneity, with a substantially lower AICc (38.66) and a better fit (R^2 = 0.91) for combined population density and income. Results indicate that dense population consistently drives brighter

[4] UK Ministry of Housing, Communities & Local Government, 2019 IMD dataset, available at: https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019. Open-access.

ALAN in northern regions, while income plays a significant secondary role in affluent southern areas.

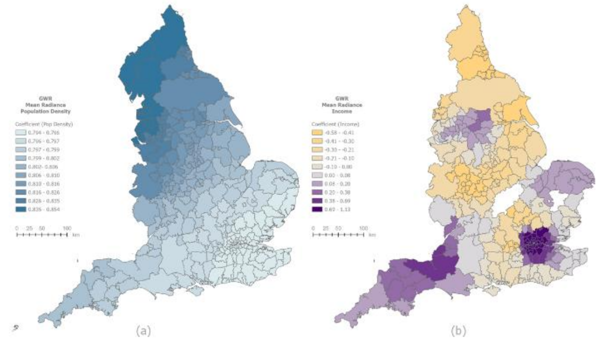

Figure 5. GWR coefficient maps of radiance against (a) population density and (b) income.

The residuals from the best-performing GWR model (Figure 6) reveal high predictive accuracy overall, but some areas, such as Halton, Walsall, and parts of Greater London, exhibit unexplained localized patterns. These findings align with prior studies noting that sociodemographic groups exposed to higher ALAN levels are not always the most deprived or marginalized (Helbich et al., 2024; Xiao et al., 2023). Instead, factors like land use, cultural lighting practices, and regulatory differences likely contribute to these variations. Further investigation into such variables is necessary to fully understand the dynamics of ALAN distribution and inform more localized, equitable lighting policies.

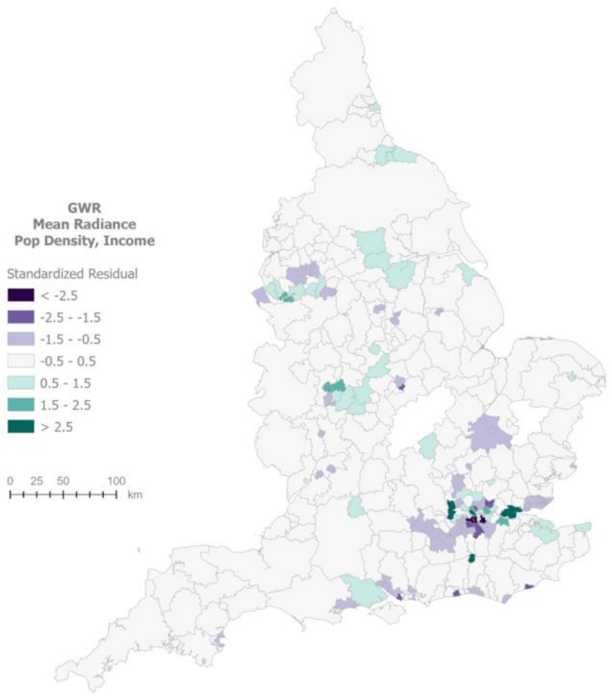

Figure 6. GWR residual map of mean radiance against combined population density and income.

4 Conclusion

This study has demonstrated significant spatial disparities in ALAN across England and their relationship with population density, income, and IMD. Population density emerged as the strongest predictor of radiance, particularly in urban areas, while income plays a localized but important role in affluent southern regions. Higher ALAN in deprived areas, likely due to outdated infrastructure, underscore the intersection of light pollution with socioeconomic inequities.

GWR implementation revealed the complexity of ALAN, suggesting the influence of other factors land use, cultural lighting practices, and regulatory differences, which require further investigation.

These findings highlight the need for localized approaches to address light pollution. Future studies incorporating temporal data and additional variables could further clarify the dynamics of ALAN and its impacts.

Declaration of Generative AI in writing

The authors declare AI tools were utilized for language editing but not for generating scientific content, research data, or substantive conclusions. All intellectual and creative work, including the analysis and interpretation of data, is original and has been conducted by the authors without AI assistance.

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Author contribution.

Margaux Elijah Neri: Conceptualization, Methodology, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization

Vicente Tang: Writing – review & editing, Supervision

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