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Measuring regional inequality using nightlight satellite data and population density for Nigeria

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Abstract: Measuring the spatial differences in regional development was the main objective of this study. To meet this objective, spatial patterns & clusters of variables, viz. nightlight & population density, were identified at the LGA level. Secondly, regression analysis between the same variables was performed to find the spatial differences in the night light. VIIRS Day/Night Band (DNB) data was chosen as the dependent variable, and UN-Adjusted Population Density data was selected as an explanatory variable. Spatial patterns & clusters were identified using spatial statistics. Global Ordinary Least Squares (OLS) linear regression was chosen to model nightlight in terms of its relationships to population density. Geographically Weighted Regression (GWR) regression was used to model spatially varying relationships between the same variables. The results show nightlight (z >97, p <0000) & population density (z >108, p <0000) are highly clustered. The R2 obtained from OLS & GWR are 0.75 & 0.85, respectively. Moreover, model variables & diagnostics results confirm the validity of both models.

Key Words*: nightlight data, population density, regional inequality.*

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Introduction

Despite Nigeria's rich endowment in natural and human resources, the country's development pace remains sluggish (Ene, 2020) and not equally distributed (Dieteren & Bonfrer, 2021). Variations in resource distribution across different regions contribute to disparities in regional economic development (Li, 2021). But, equal development of regions is vital for eco and sustainable development (Gechbaia et al., 2021). Unequal development in Nigeria is a pressing issue that has persisted for decades, driven by a complex interplay of factors, including geography, history, governance, and resource distribution (Hodgson, 2018). Nigeria's diverse geographic landscape, which spans from arid northern regions to lush southern areas, has contributed significantly to regional disparities in development

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(Adepoju, 2006). Historical legacies play a pivotal role in these disparities. Nigeria's colonial past, which included British rule in the south and less direct rule in the north, led to differential access to education, infrastructure, and economic opportunities. The effects of these historical imbalances continue to reverberate today, perpetuating unequal development (Suberu, 2001).

Resource allocation and management have been another significant driver of regional inequality. The southern regions, particularly the Niger Delta, are rich in oil reserves, which have historically provided a substantial portion of the country's revenue. However, the benefits of this resource have not been equitably distributed, leading to socio-economic and infrastructural deficits in other regions (Eboh, 2014). Additionally, governance issues, including corruption, mismanagement of resources, and weak public institutions, have exacerbated the problem of unequal development. These issues hinder effective policy implementation and public service delivery, disproportionately affecting regions already struggling with development challenges (Omotola, 2011).

The consequences of unequal development are profound. Disparities in income, education, healthcare, and living standards persist, fostering social unrest and political tensions (Oladipo, 2006). Addressing these disparities is a critical challenge for Nigeria's government, requiring strategic and targeted policy interventions (Egwu, 2017).

Satellite-based nighttime illumination data can be used to map human activities (Levin et al., 2020), economic activities (Anand & Kim, 2021), local economic growth (Bertinelli & Strobl, 2013), settlement activities (Bluhm & Krause, 2022) additionally, this methodology offers an alternative for considering economic factors in less-developed countries, where data accessibility can often be challenging. (Weidmann & Schutte, 2017). Nightlight and Machine learning help estimate development where data are not precise (Otchia & Asongu, 2020). Population and nightlight (NLT) data have been used to visualize the development index (Zhao et al., 2021). Nightlight data (NLT) opens up new possibilities for real-time measurement of regional disparities by facilitating the development of the Nightlight Development Index (NLDI) (Ivan et al., 2020). It is easy now to monitor and evaluate energy consumption with night light data (Xiao et al., 2018). NLT has many applications, such as estimating population and GDP, urban mapping, and monitoring fire and war. Remotely sensed man-made lighting radiances can provide a level of human activity during the night (Ma, 2018). A high positive association exists between night lights and GDP estimates (Bhandari & Roychowdhury, 2011). Regular observations of night lighting and its profound study have made it easy to study socio-economic dynamics (Krikigianni et al., 2019). The use of NLT is growing daily in economic activity estimation (Prakash et al., 2019) and in GIS and remote sensing studies. Human-created light provides a unique footprint of human activities and settlements (Zheng et al., 2018). The satellite sensor detecting nighttime light data is supposed to be a reliable source for mapping urban areas across large regions (Alahmadi & Atkinson, 2019).

Night light data offers a more straightforward approach to quantifying urbanization levels. Its advantage lies in accurately reflecting the spatial extent of urban land and effectively depicting the spatial pattern of socioeconomic activities within urban areas (Wang et al., 2020).

In developing countries, incorporating energy planning into overall development strategies is crucial due to the rapidly growing rates of economic expansion and increasing energy demand (Lee et al., 2020). Currently, Nighttime Light (NLT) data is gathered by two satellite sensors: DMSP-OLS and VIIRS, as noted by Zheng et al. (2019). The VIIRS sensor's NLT data offers a higher spatial resolution than the DMSP-OLS night light data, as highlighted by Small et al. (2013). A significant issue with DMSP-OLS is the extensive blurring in its images, often referred to as 'overglow' or 'blooming', a point raised by Abrahams et al. (2018). Since April 2012, NTL data from VIIRS has been available, effectively overcoming some DMSP-OLS limitations, as Sahoo et al. (2020) mentioned. Therefore, this research employs VIIRS nighttime light data. The use of VIIRS-based data is crucial for investigating the spatial pattern of the urban system using night light data, as Zhong et al. (2018) have indicated.

The low power generation in Nigeria has delayed its economic growth (Emovon et al., 2018). The goal of the power sector in Nigeria is to transmit electrical power to all regions professionally (Samuel et al., 2020). Researchers have used night light data to assess the regional differences in power supply (Fan et al., 2014). Researchers have used night light data to determine the regional differences in power supply (Elvidge et al., 2012).

The general objective of this study was to measure regional inequality in the development process of Nige-ria. Four specific objectives were framed to meet this objective: first & second, to find the pattern and clusters of night light data and population density; and third and fourth, to model night light distribution about population density using OLS & GWR, respectively.

Material and Methods

This research was carried out at the district level across Nigeria, located on Africa's western coast. Nigeria showcases diverse geographical features and a range of climates, varying from dry to humid equatorial conditions. The southeastern part of Nigeria experiences hot and moist conditions for most of the year, whereas the northwest and inland areas are predominantly dry. A savanna climate prevails in the west and north, characterized by distinct dry and wet seasons, while the far north exhibits a steppe climate with lower precipitation levels (Ajayi et al., 2020). Unequal development in Nigeria is a pressing concern with far-reaching implications. Several factors contribute to this disparity, including variations in natural resources, historical legacies, infrastructure, and economic opportunities. The northern regions, for instance, face challenges associated with arid climates and limited access to arable land, while the southern regions often benefit from more favourable conditions for agriculture and oil wealth. These disparities have led to inequalities in income, education, healthcare, and overall quality of life. In 2020, population density in Nigeria exhibited significant variation at the Local Government Area (LGA) level, reflecting diverse demographic patterns across the country. Urban areas, particularly Lagos, recorded very high population densities, with some LGAs exceeding 20,000 people per square kilometre due to intense urbanization and economic activities. Conversely, rural regions, such as those in the northern states of Yobe and Taraba, experienced very low population densities, often below 50 people per square kilometre, attributed to expansive land areas and lower urban development. This stark contrast highlights Nigeria's uneven distribution of population density, driven by factors such as urbanisation, economic opportunities, and regional development disparities.

Understanding these regional development differences is crucial for several reasons. Firstly, it informs policymakers about the specific needs and challenges faced by different regions, facilitating the allocation of resources and the design of targeted development programs. Secondly, it can help address social and political tensions arising from unequal development, contributing to social cohesion and stability.

This study, conducted at the district level in Nigeria, is instrumental in shedding light on the spatial variations in development within the country. Using spatial analysis and regression techniques provides a data-driven understanding of factors contributing to regional disparities, such as the relationship between nightlight and population density.

With a more granular understanding of these dynamics, Nigeria's leaders can make more informed decisions to promote balanced development and improve the livelihoods of citizens across the nation, ultimately fostering economic growth and social well-being. In essence, this study's findings have the potential to influence policy reforms that can address long-standing disparities, promoting a more equitable and prosperous future for Nigeria as a whole.

Two primary datasets were used to measure regional inequality in Nigeria for 2020. The first dataset, the Night Light data, captures information about nightlight emissions. This data was stored in TIFF format with a band named "avg_rad." It measured night light in Watts per square centimetre per steradian and represented the mean monthly values for 2020. The second dataset was Population Density data, which estimates the number of individuals per 30 arc-second grid cells and is also in TIFF format. This data helps us understand how people are distributed across different areas in Nigeria in the same year. By combining these datasets, researchers will gain valuable insights into the regional disparities and inequalities in economic development and population distribution within Nigeria during 2020.

Table 1. Data Source and Resolution of Satellite Images

Dataset	Source	Resolution	Date
Night Light Data	VIIRS Day/Night Band	2.8 km	2020
Population Density	Gridded Population of the World (GPW), v4	30 arc-second grid cells	2020

Source: Earth Engine Catalog, 2024

To measure regional inequality in Nigeria using nightlight satellite data and population density, we utilized Google Earth Engine (GEE) and ArcGIS. Nightlight data from the Visible Infrared Imaging Radiometer Suite (VIIRS) was collected using GEE, which has cloud-based capabilities for accessing and processing extensive satellite datasets. The pre-processed nightlight data was then imported into ArcGIS, where various spatial analyses were performed. ArcGIS facilitated tasks such as reprojecting data, conducting zonal and hot spot analyses, and visualising the relationship between nightlight intensity and population density. This integration of GEE for data collection and ArcGIS for spatial analysis enabled a comprehensive examination of regional inequality across Nigeria.

The "Global Moran's I" statistics were used to predict the pattern of nightlight and population density at the local government administrative level in Nigeria. This method assesses spatial autocorrelation by simultaneously considering the location and attribute values. The resulting pattern could be dispersed, clustered, or random, contingent on the features' specific location and attribute values. The Moran's I statistic, which quantifies spatial autocorrelation, is delineated in equations 1 to 5.

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \quad (1)$$

In this context, zi represents the deviation of a feature's attribute from its mean, while the spatial weight between feature j and i is denoted. The term n stands for the total number of features. S0 refers to the aggregate of all spatial weights.

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \tag{2}$$

The z_i-score for the statistic is computed as:

$$z_I = \frac{I - E[I]}{\sqrt{V[I]}} \tag{3}$$

Where:

$$E[I] = -1/(n-1) \tag{4}$$

$$V[I] = E[I^2] - E[I]^2 \tag{5}$$

The inverse distance & Euclidian distance method was chosen to conceptualise spatial relationship parameters. Distance Threshold was given as 71,668.8 Meters, representing the maximum distance over which spatial interactions were considered significant for the analysis.

The statistic "Getis-Ord Gi*" was used to identify the hot spots for the nightlight and population density dataset. The resultant p-values and z-scores indicate low or high values cluster spatially, eq. 06 to 08.

$$G_i^* = \frac{\sum_{i=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{i=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \tag{6}$$

In this formula, xj indicates the attribute value of feature j, and wij represents the spatial weight between feature i and j. The variable n signifies the total count of features, and the following details are elaborated upon further in the text:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{7}$$

$$G_i^* = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2} \tag{8}$$

This statistic is the z score, so no further calculation is required.

Ordinary least squire (OLA) regression was used to find the nightlight global variability in relation to population density within Nigeria (eq. 9):

$$\gamma = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots \beta_n X_n + \varepsilon \tag{9}$$

In this equation, γ stands for the dependent variable, β denotes the coefficients, X represents the explanatory variables, and ε indicates the random error. Geographically weighted regression (GWR) was used to find the local variability of nightlights in relation to population density at the LGA level in Nigeria. OLS constructs a single equation, but GWR constructs separate by taking variables of features under the bandwidth of each target feature. The shape and size of the bandwidth chosen are given as follows. Kernel type: For the spatial analysis, an adaptive kernel type, specifically the Gaussian kernel, was chosen. The number of neighbouring features determines this kernel's functioning. In areas where features are densely distributed, the spatial context defined by this kernel is smaller.

Conversely, the spatial context becomes larger in regions with sparse feature distribution. Bandwidth method: CV (cross-validation) was selected, and the tool found the optimal distance or number of neighbours for the analysis.

Results and Discussion

Spatial Pattern of Nightlight and Population Density

The result indicates that night light in Nigeria's LGA level is too clustered (z = 97.01). Given the z-score of 97.01, there is a <1% likelihood that this clustered pattern may be due to random chance. This means that the distribution of night lights in Nigeria's LGAs is not random. Instead, night light appears to be concentrated in certain areas of LGAs. These clusters may represent regions with higher economic activity, urbanisation, or infrastructure development, resulting in more illumination during the night. A high z-score indicates an extreme deviation from the mean. In this case, a z-score of 97.01 is exceptionally high, suggesting that the clustering of night light is far from what would be expected by random chance. These findings are essential for understanding the spatial distribution of development and can affect policy decisions to address regional disparities and promote balanced growth across the country.

Population density at the LGA level in Nigeria is highly clustered (z = 108.8). Given the z-score of 108.18, there is a <1% probability that this highly clustered pattern may be due to random chance. This means that the distribution of population density in the LGAs of Nigeria is not random. Instead, it indicates that people are concentrated in certain areas or LGAs, and there are notable spatial patterns. These clusters may represent regions with higher population density due to urbanisation, economic opportunities, or historical settlement patterns. These findings are essential for policymakers as they highlight areas where the population is concentrated, and targeted policies may be needed to address issues related to infrastructure, services, and resource allocation in densely populated regions.

Hot Spots of Night Light and Population Density

The result of the night light data hotspots is given in Figure 1, which indicates that there are 04 well-marked hot spots for the night light. Lagos has the highest mean nightlight intensity of 12.88 Watts/cm²/sr, signifying its status as a prominent urban and economic centre. Delta, Kano, Rivers, Edo, Ogun, Bayelsa, and Jigawa follow in descending order. These rankings provide insights into the varying degrees of urbanisation, economic activity, and development across these states, which have implications for understanding regional disparities and policy considerations.

The result of hotspots of population density data is presented in Figure 2, indicating two well-marked hotspots of population density. These hotspots are organised based on different confidence levels, with each section detailing the number of Local Government Areas (LGAs) and the mean population density. At a 99% confidence level, Lagos has 20 LGAs with an average population density of 13,635 people per 30 arc-second grid cells, signifying a high population density across its LGAs. Similarly, Kano has 38 LGAs with an average population density of 3,241, indicating substantial population concentrations. Ogun has 14 LGAs with a mean population density of 932, which is also relatively high, whereas Jigawa, with only 2 LGAs, has a mean population density of 370, indicating lower population density areas. The total number of LGAs considered at the 99% confidence level is 74, with a combined average population density of 4,544.

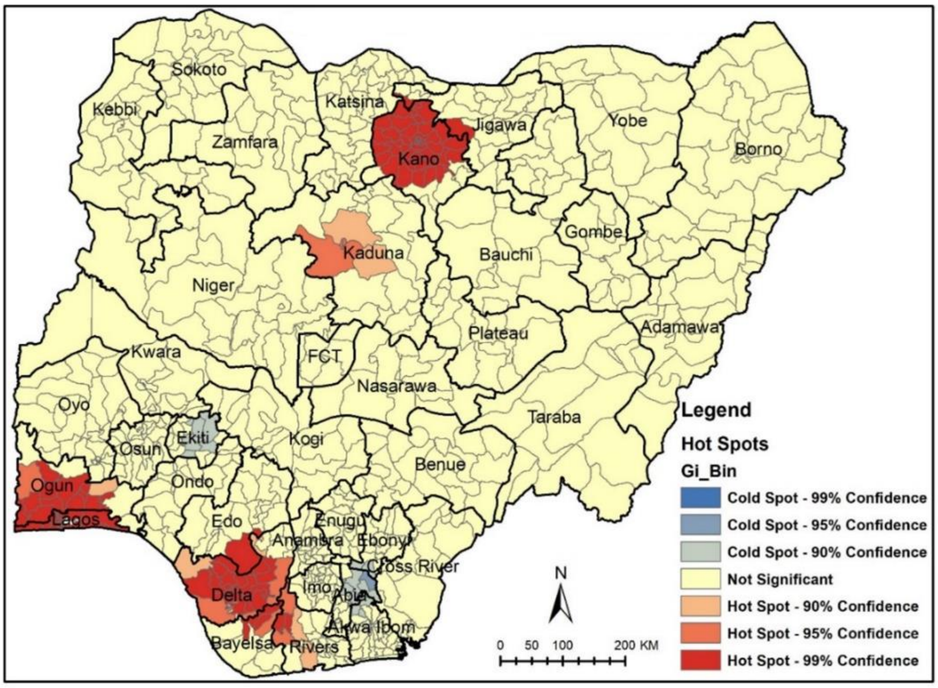

Figure 1. Hot Spots of Night Light

Source: NOAA_VIIRS_DNB_MONTHLY_V1_VCMSLCFG

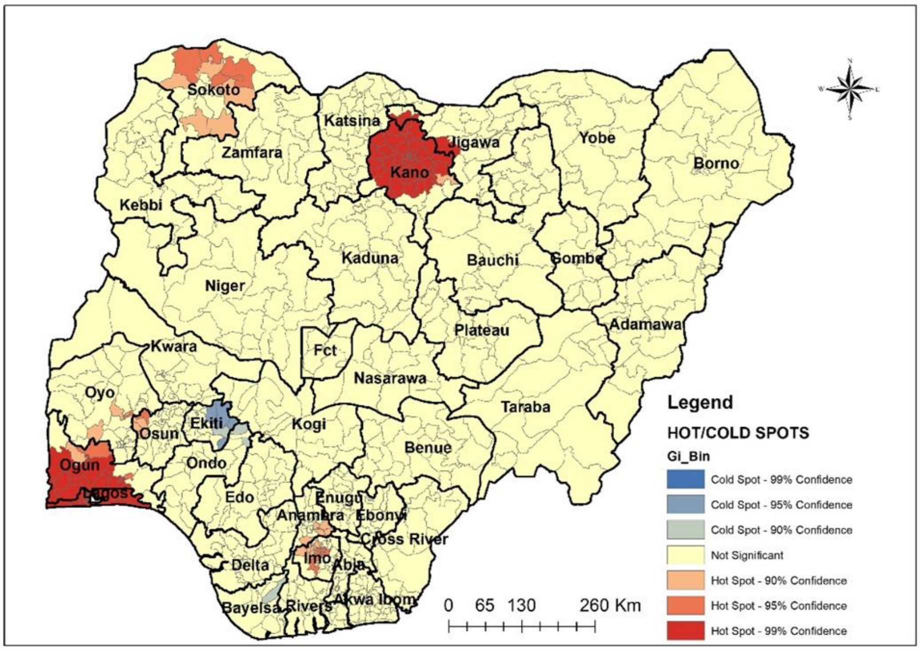

Figure 2. Hot Spots of Population Density

Source: CIESIN/GPWv411/GPW_Population_Density.

At a 95% confidence level, Oyo has 6 LGAs with an average population density of 4,166. Ogun is represented again at this confidence level with 3 LGAs and a mean population density of 430. The total number of LGAs considered at the 95% confidence level is 9, with a combined average population density of 2,298. At a 90% confidence level, Oyo has 9 LGAs with a mean population density of 4,378, while Osun, at the same confidence level, has 6 LGAs with a mean population density of 483. The total number of LGAs considered at the 90% confidence level is 15, with a combined average population density of 2,431.

Figure 2 essentially provides insights into the distribution of population density across Nigerian states at different confidence levels. Higher population densities at specific confidence levels suggest regions with more significant population concentrations, while lower densities indicate areas with relatively fewer inhabitants. This information is vital for understanding the country's population patterns and regional disparities.

Spatial relationships between Night Light & Population Density

Figure 3 presents a comprehensive analysis of standardised residuals of nightlight (OLS) for various states and Local Government Areas (LGAs) in Nigeria. These are a crucial indicator of how the actual nightlight levels differ from those predicted by an Ordinary Least Squares (OLS) regression model.

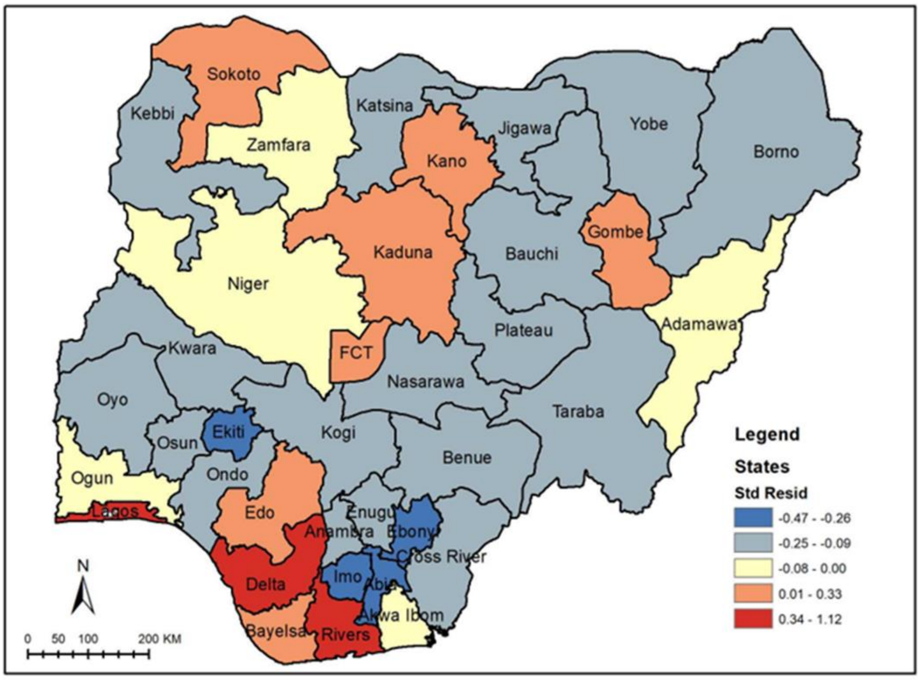

Figure 3. Standard residuals at state level

Source: Ordinary Least Squares (OLS) model

In the context of this analysis, it's important to note that lower values of standardised residuals indicate a situation where the actual nightlight levels are significantly lower than the values predicted by the model, which may suggest areas with less nighttime illumination relative to what would be expected based on the population. On the other hand, higher positive values of standardised residuals suggest areas where actual nightlight levels are significantly higher than the model's predictions concerning population density, indicating regions with more extensive or brighter nighttime illumination than what could be explained by population alone.

For instance, Lagos stands out as an extreme case with a high positive standardised residual (StdResid), indicating that it has exceptionally high nightlight levels beyond what population density would predict, possibly due to its significant economic and urban centre status. Conversely, areas with low standardised residuals, such as Abia, Aba South, and Ugwunagbo, have nightlight levels significantly below what population density alone would predict. This could imply factors like limited urbanisation, economic activity, or infrastructure development in these regions. This analysis is valuable for understanding discrepancies between actual nightlight levels and what can be expected based on population density, shedding light on the presence of “outliers” regarding nighttime illumination across different states and LGAs in Nigeria.

Spatially varying relationships between Night Light & Population Density

Negative standardised residuals indicate areas where the actual nightlight levels are notably lower than predicted by the GWR model (Figure 4). These areas may have lower nightlight levels relative to population density, suggesting potential factors like lower economic activity or less urbanisation. Conversely, positive standardised residuals point to areas with higher actual nightlight levels than the model would predict based on population density alone. This may indicate regions with more extensive or brighter nighttime illumination, potentially due to economic activity, infrastructure development, or other contributing factors. For instance, states like Lagos and Kano exhibit high positive standardised residuals, suggesting they have significantly brighter nightlight than population density alone would suggest. Lagos, a significant economic and urban centre, has exceptionally high nighttime illumination. On the other hand, areas like Girei, Yola South, or some LGAs in Akwa Ibom show notably negative standardised residuals, indicating lower nightlight levels compared to what would be expected based on population. Further investigation into these areas could help understand the reasons behind these discrepancies.

The Geographical Weighted Regression (GWR) model offers advantages over the Ordinary Least Squares (OLS) model, particularly when analysing spatial data. GWR accounts for spatial heterogeneity, allowing for examining variations in the relationship between variables at different locations. In analysing nightlight data, it's essential to consider that the relationship between population density and nightlight may vary across regions. GWR can capture this spatial variation, which OLS cannot.

GWR provides localised parameter estimates. This means that you get a unique set of parameter estimates for each specific location (e.g., state or LGA). This is valuable for understanding the nuances of how population density and other factors influence nightlight at a local scale. OLS provides a single set of parameters for the entire dataset, which may not adequately capture the variations present in spatial data. The results demonstrate that GWR can help identify spatial outliers with its standardised residuals. Areas with notably high or low standardised residuals can be interpreted as locations with unexpected nightlight levels in relation to population density. This information is critical for understanding regional disparities and identifying areas where additional investigation or policy intervention may be needed. GWR often results in a better model fit, as it accounts for spatial autocorrelation. Spatial autocorrelation occurs when values in one location are correlated with values in nearby locations. OLS assumes that observations are independent, which can lead to issues in spatial data analysis. GWR considers spatial autocorrelation, leading to more accurate and locally relevant parameter estimates.

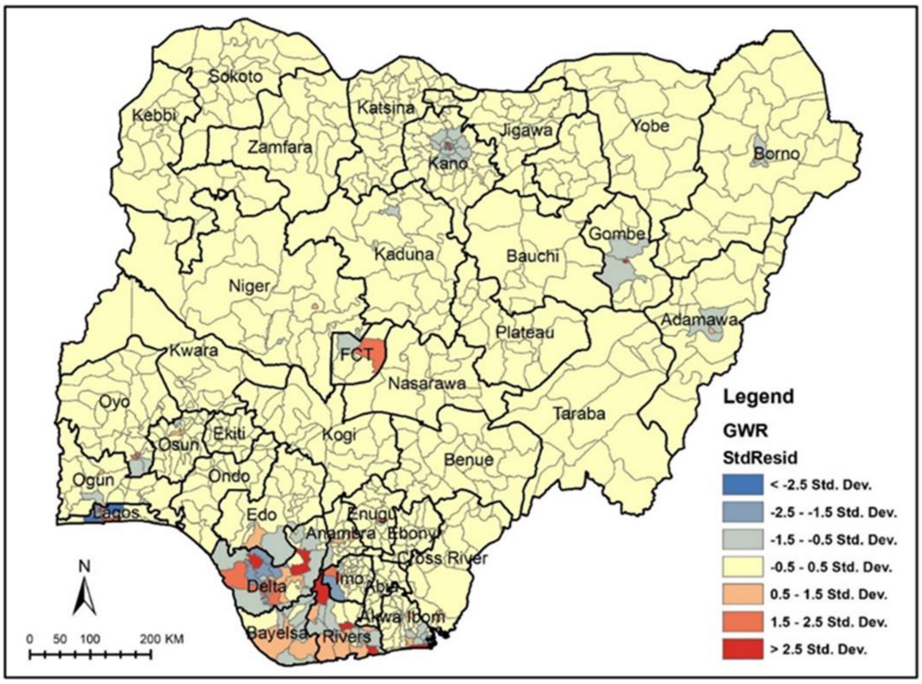

Figure 1. GWR - Standard Residual Map

Source: Geographical Weighted Regression (GWR) model.

So, GWR is a powerful tool for spatial decision-making and policy development. Policymakers and researchers can make informed decisions and allocate resources effectively by providing insights into how variables relate at the local level. This is particularly important when addressing regional disparities and inequalities.

Conclusions

Based on the VIIRS/DNB nighttime lighting data, this paper studies the spatial pattern, clusters, and spatial differences in the night light pattern in relation to population density at the LGA level in Nigeria. The study addresses the critical need to assess and understand the disparities in regional development. Regional development is an essential concern for policymakers, as it can impact economic growth, living standards, and social well-being. The study provides valuable insights into development across different regions by measuring spatial differences. The study identifies spatial patterns and clusters of variables, specifically nightlight and population density, at the Local Government Area (LGA) level. This is significant as it helps recognise areas with similar characteristics or issues, which can inform targeted policy interventions and resource allocation. The study reports high values of R2 for both the Ordinary Least Squares (OLS) and GWR models, indicating that the chosen models provide a good fit for the data. This adds credibility to the results, making them more robust and reliable. The results of this research show that the following: (1) The pattern is highly clustered; (2) There are four clusters of Nightlight but two clusters of population density; (3) The variability of night light distribution was significantly explained by the density of population. The use of nightlights is essential for identifying underdeveloped areas and coordinating the country's development. Therefore, it is evident that the study of the regional pattern of the night light at LGA level has high significance and value. The VIIRS/DNB nighttime lighting satellite data has unparalleled advantages for monitoring development and analysing spatial patterns of nightlight data. This research paper utilised diverse data sources, including UN-adjusted population density, Local Government Area (LGA) level administrative boundaries of Nigeria, and night light data. It employs advanced statistical tools and methodologies such as cluster analysis, pattern analysis, and regression analysis. These techniques are instrumental in extracting nighttime light thresholds. The processes involved in data calculation and the analysis of research findings are characterised by a high degree of feasibility. Both OLS and GWR were used to analyse spatial relations between night light and population density. GWR was found to be a better model for this spatial data analysis, especially when dealing with variations in relationships between variables across different locations. Its ability to provide localised insights, identify spatial outliers, and offer a better fit for spatial data makes it a valuable tool for understanding and addressing regional diversity and inequalities, as demonstrated in the provided tables.

Despite its utility, the practical application of this methodology faces challenges, such as the low resolution of nighttime lighting satellite data and population density data. This leads to reduced data accuracy in less urbanised areas. Acquiring more detailed data through higher-resolution sources would be beneficial. Quantitative research can potentially enhance this situation, suggesting that further research in this area should be pursued.

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