

From Light to GDP: A Study of Night-Time Light as an Indicator of Economic Development*

Near One-to-One Relationship Between Night-Time Lights and GDP. Weaker Statistical Systems Show Diminished Correlation

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We examine the relationship between night-time light (NTL) intensity, captured by satellite imagery, and GDP across countries over decades. Analyzing data from 1992 to 2001, we find a strong, near one-to-one correlation between NTL and GDP, which weakens in countries with lower statistical capacity. Population and manufacturing share of GDP are also correlated with NTL but explain less variation than GDP. Using recent satellite imagery, this study revisits the NTL-GDP relationship over time, reaffirming NTL as a valuable proxy for economic activity in regions with unreliable or unavailable GDP metrics.

1 Introduction

Economic growth measurement is central to policymaking, research, and international comparisons. Despite its importance, GDP figures, widely used as a benchmark for economic activity, are often criticized for inaccuracies, particularly in contexts where governance systems are less transparent. In authoritarian regimes, GDP data is vulnerable to manipulation for political ends, while in low-capacity states, weak statistical systems limit the reliability of national accounts. These challenges motivate the search for alternative indicators of economic activity. Night-Time Light (NTL) intensity, derived from satellite imagery, offers a compelling solution. Unlike GDP, NTL data is immune to tampering and provides a direct measure of human and industrial activity. By capturing emissions from streetlights, industrial areas, and residential zones, NTL reflects patterns of development that cannot be easily concealed or fabricated.

Numerous studies have explored the relationship between NTL and GDP, particularly during the 1990s and early 2000s. These earlier studies primarily relied on the Defense Meteorological Satellite Program (DMSP) dataset, which was not originally designed for research purposes and suffered from technical limitations. More recent advancements, however, have introduced the Visible Infrared Imaging Radiometer Suite (VIIRS) dataset, which offers significantly improved quality, including better spatial resolution, radiometric calibration, and fewer issues with data saturation. With this enhanced dataset, spanning a broader temporal range and covering a larger sample of countries, it is now possible to revisit and expand upon earlier findings. This explore how the correlation between NTL and GDP has evolved, with particular attention to the moderating role of statistical capacity in different countries. Using fixed effects models, we aim to study the strength of the NTL-GDP correlation and assess its variation

*Code and data are available at: <https://github.com/shamayla38/EconomyLightCorrelation>.

across countries grouped by statistical capacity. In particular, we aim to estimate the elasticity of GDP with respect to NTL intensity, capturing how changes in light emissions correspond to economic output, while controlling for country and year effects.

We began by attempting to control for key variables such as population and the manufacturing share of GDP to refine our estimates of the NTL-GDP relationship. However, given the high multicollinearity between GDP, population, and manufacturing share, it was not feasible to include all these variables in the same model. Instead, we opted for separate regressions to isolate their unique relationships with NTL. Our results show a strong overall correlation between NTL and GDP, with coefficients consistently positive across models and R-squared values exceeding 0.90 in most cases. In addition to GDP, both population and manufacturing share of GDP were significantly correlated with NTL. While the relationship was not as strong as that observed with GDP, the models incorporating these variables explained a substantial proportion of the variation in NTL, with over 90% of the variation in light intensity accounted for in most cases.

To study the variation in the NTL-GDP relationship by statistical capacity, we employed a dual approach. First, we introduced interaction terms between GDP and statistical capacity grades to capture heterogeneity within a single framework. Second, we ran subset regressions for countries grouped by statistical capacity grade, allowing us to analyze dynamics specific to each group. Our findings reveal that while the interaction model provides a unified overview, the subset regressions better capture the unique challenges faced by countries with weaker statistical systems. In particular, countries with lower statistical capacity exhibit greater variability in residuals and weaker correlations between NTL and GDP, underscoring the need for tailored analyses in these contexts.

The structure of the paper is as follows. Section 2 outlines the data sources, the methods used to process and clean raster data from TIFF files, and the integration with World Bank data, along with a summary of the dataset. Section 3 examines the distribution of key variables. Section 4 visualizes and discusses the relationships between night-time light (NTL) and the variables of interest. Section 5 presents the different models used in the analysis, while Section 6 summarizes and interprets the model results. Section 7 discusses the implications of the findings and provides a broader discussion on uses and challenges of NTL. Finally, the appendix - Section 8 includes supplementary figures and tables, such as the correlation matrix, model diagnostics, and an extended discussion on the measurement of night-time light.

2 Data

We collected data from multiple sources to analyze the relationship between night-time light intensity and GDP growth. The primary dataset is a harmonized global night-time light (NTL) dataset spanning from 1992 to 2018, developed by Li et al. (Li et al. 2020). The dataset combines observations from two satellite systems: DMSP/OLS (1992–2013) and VIIRS (2012–2018). To ensure consistency across years, they addressed differences in spatial resolution and saturation between the two systems by inter-calibrating DMSP data and simulating DMSP-like VIIRS observations. The resulting dataset provides annual Digital Number (DN) values, representing night-time illumination intensity, as GeoTIFF files.

We also sourced GDP, manufacturing share of GDP, and population data from the World Bank's World Development Indicators (WDI) (The World Bank 2024), measuring GDP in purchasing power parity (PPP) for comparability across countries. Additionally, we incorporated the Statistical Performance Indicator (SPI), which evaluates national statistical systems across five pillars: data use, data services, data products, data sources, and data infrastructure. (The World Bank 2024) A thorough discussion on how we organised the data set is given in Section 2.2.

2.1 Measurement

Night-time light intensity, which reflects human activity, is indirectly measured by satellite sensors onboard the DMSP/OLS and VIIRS systems. These satellites capture light emissions from streetlights, industrial complexes, and residential areas, converting this physical phenomenon into Digital Number (DN) values. The brightness levels are then transformed into quantifiable data, which are stored in GeoTIFF format for further analysis. DMSP/OLS, operational since the 1970s, used low-light imaging to detect artificial lights but had limitations such as coarse resolution and sensor saturation (C. D. Elvidge et al. 1999). VIIRS, launched in 2012, provided better spatial resolution and could capture a wider range of light levels, with improved algorithms to filter out unwanted noise and natural light sources.(C. Elvidge et al. 2017). The harmonized version of these two datasets, combining data from DMSP/OLS and VIIRS, has been used by researchers for analysis.

GDP is measured as the total economic output of a country, adjusted for purchasing power parity (PPP) to standardize across different national economies. This transformation from an elaborate economic reality into a single numerical value is done through extensive national accounting systems, with data collected by governments through economic surveys, reports, and censuses. Population figures, reflecting demographic changes and the size of human capital, are also derived from national censuses and are measured in absolute numbers. Meanwhile, the manufacturing share of GDP is calculated by extracting relevant economic data, representing the portion of a country's GDP generated by the manufacturing sector. The World Bank sources all these data from national accounts.

2.2 Data Extraction and Cleaning

The data preparation began with extracting night-time light (NTL) intensity values from GeoTIFF files using Python' 'Rasterio' (Gillies et al. 2013) package. This process involved reading annual TIFF files to obtain Digital Number (DN) values, representing light intensity, along with their corresponding latitude and longitude coordinates. This resulted in a spatial dataset detailing global NTL distribution for each year.

To associate each observation with a specific country, the extracted data were merged with a global shapefile of country boundaries through spatial join using 'geopandas' (Jordahl et al. 2020) in python (Python Software Foundation 2023). Each latitude-longitude pair was assigned to the country in which it was located, and observations without an assigned country—primarily from international waters—were removed. Subsequently, to create an aggregate annual measure of NTL intensity for each country, all observations within a country were summed to calculate the total light emitted annually.

The World Bank data, including GDP, manufacturing share of GDP, and population, were processed by standardizing country names to ensure consistency across datasets. For instance, discrepancies like 'Yemen' versus 'Yemen, Rep.' were resolved. The data were then transformed from a wide to a long format using pandas' 'melt' function, facilitating easier merging with the NTL data.

To assess how the correlation between night-time light (NTL) intensity and GDP varies among countries with differing levels of statistical capacity, we first to group countries together based on a measure of each country's statistical capacity. We used the World Bank's Statistical Performance Indicators (SPI). We calculated the average SPI score for each country across all the years SPI was available for and assigned grades based on these averages: scores of 80 and above received an 'A', scores between 60 and 79 a 'B', scores between 40 and 59 a 'C', scores between 20 and 39 a 'D', and scores below 20 an 'F'. A glimpse of the dataset is presented in Table 1.

Table 1: Sample of the dataset showing key variables used in the analysis

Country	Year	Night Lights (DN)	GDP (PPP)	Manufacturing Share	Population	Grade
Afghanistan	2002	37956	37931379899	18.822752	18.822752	C
Albania	1996	54902	17326597422	4.857952	4.857952	B
Algeria	1999	1634753	344181000000	34.479053	34.479053	C
Angola	1995	47138	72399259721	3.646281	3.646281	C
Antigua and Barbuda	1992	4162	1374028894	2.036987	2.036987	C
Argentina	1992	1427787	656388000000	21.859132	21.859132	B
Armenia	2012	160580	35673112560	9.424759	9.424759	A

Table 2: Summary Statistics of Data from year 1995 and 2020

	1995 (N=188)		2020 (N=189)	
	Mean	Std. Dev.	Mean	Std. Dev.
DN	1 412 963.5	5 631 142.1	2 971 421.4	9 552 808.9
GDP	369 356 559 423.2	1×10^{12}	776 024 587 843.4	3×10^{12}
Manufacturing	14.8	7.2	11.7	7.0
Population	14.8	7.2	11.7	7.0

DN refers to total average night-time light intensity emitted by a country in a year, GDP is measured in PPP, and Manufacturing refers to the manufacturing share of GDP.

2.3 Summary Statistics

It is more meaningful to examine the summary statistics year-wise to capture temporal variations in the data, as the variance across all years is substantial. Table 2 displays the summary statistics for selected years, showing significant growth in average night-time light intensity (DN), GDP (measured in PPP), and population from 1995 to 2020. An especially intriguing observation is that both night-time light intensity and GDP grew by almost exactly the same proportion—2.1 times—between 1995 and 2020 (DN increased by 2.102 times and GDP by 2.101 times). The summary statistics of the rest of the years are given in appendix.

3 Variable Description

3.1 Night Time Lights Data

Nighttime light (NTL) distribution and intensity often vary significantly by population density, GDP, and levels of urbanization. When comparing countries with similar population sizes and land areas, the disparity in NTL intensity vividly reflects income inequality. A striking example is the contrast between North and South Korea, where South Korea's GDP per capita is over 50 times greater than that of North Korea, manifesting in the stark difference in nighttime illumination. In Figure 1, using NASA's Worldview NTL imagery, this difference of GDP is clearly visible, with South Korea brightly

lit compared to its nearly dark northern neighbor. Similarly, Myanmar and Thailand, with comparable populations and land area, show a distinct NTL difference; Thailand's higher GDP and urbanization are evident in its dense and widespread lighting compared to Myanmar's relatively sparse illumination.

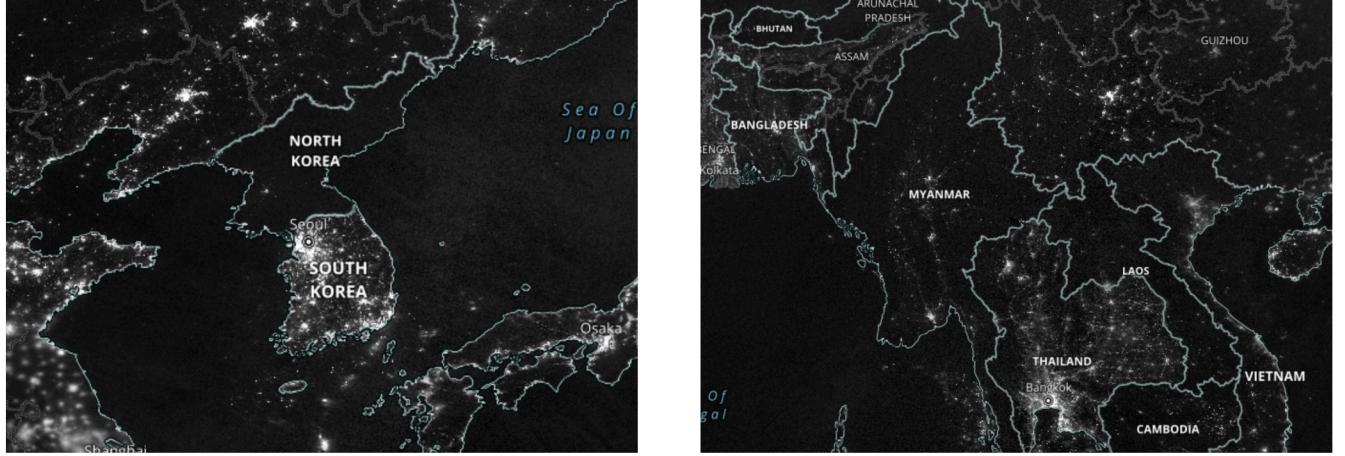


Figure 1: Night-time light intensity highlights stark contrasts in economic development: the profound disparity between North and South Korea, and the significant difference between Myanmar and Thailand. (*Source: NASA Worldview*)

Total night-time light (NTL) values for countries exhibit a highly skewed distribution due to the presence of a few highly luminous regions. In Figure 2, we observe that after applying a log transformation, this distribution becomes relatively normal, making it more suitable for comparative and statistical analysis

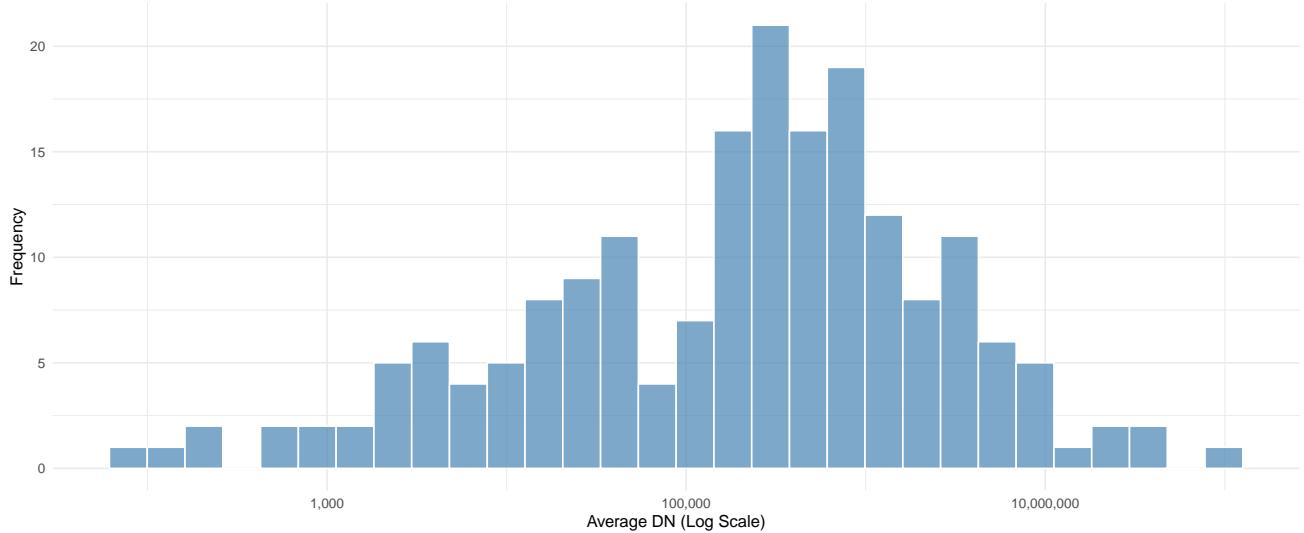


Figure 2: Distribution of log-transformed average nighttime luminosity (DN) by country over the past 30 years, showing variations in average brightness levels across nations.

3.2 GDP

To visualise GDP distribution across numerous countries, we categorized them into UN-defined SDG regions and examined the GDP distribution for 2012-2020. The Figure 3 shows that Europe and Northern America have the highest GDP levels, followed by Eastern and South-Eastern Asia and Latin America and the Caribbean, while Sub-Saharan Africa, Oceania, and Central and Southern Asia show significantly lower GDP levels. We would expect similar variations in night-time light intensity, with regions of higher GDP likely exhibiting brighter and more widespread night-time illumination. This connection underscores how night-time light can serve as a proxy for economic activity and development, reflecting the stark differences across regions.

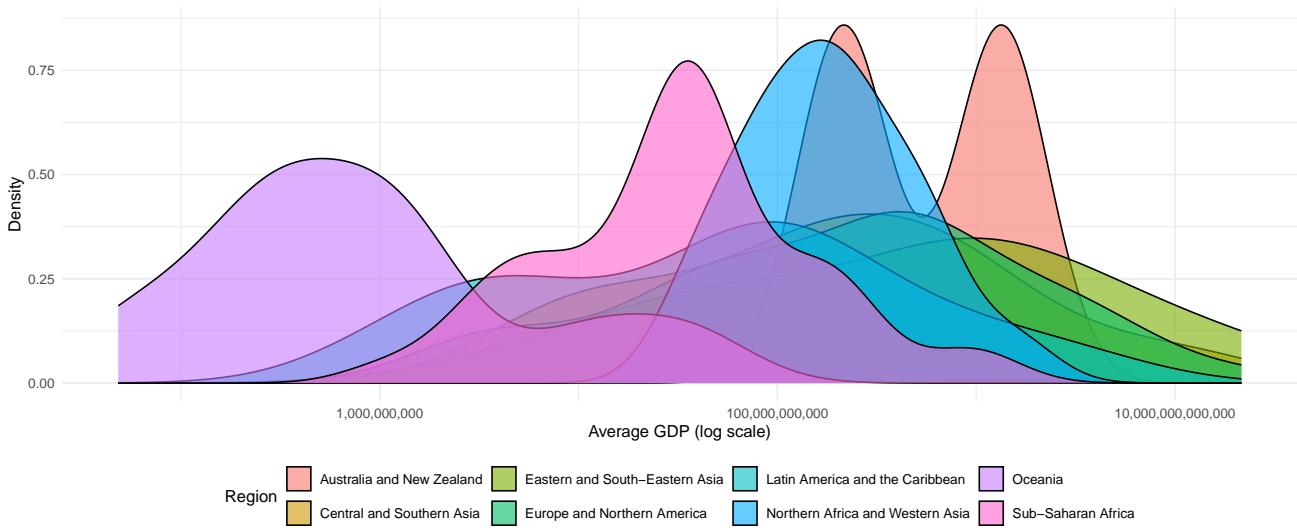


Figure 3: Density plot of average GDP (2012-2020) by region, illustrating Europe and Northern America with the highest GDP, followed by Eastern and South-Eastern Asia and Latin America and the Caribbean, while Sub-Saharan Africa, Oceania, and Central and Southern Asia exhibit significantly lower GDP levels.

3.3 Manufacturing Share of GDP of Country

Night-time light intensity is expected to vary with the share of manufacturing in a country's GDP, as higher manufacturing activity typically involves more factories, industrial areas, and infrastructure requiring artificial lighting. Figure 4 compare the distribution of manufacturing's share of GDP for 1993 and 2020, highlighting notable differences over time. In 1993, the distribution of manufacturing's share of GDP appears broader, with more countries exhibiting higher manufacturing shares. By 2020, the distribution has shifted, with a majority of countries clustered around a lower manufacturing share, though a few outliers still exhibit significantly high values.

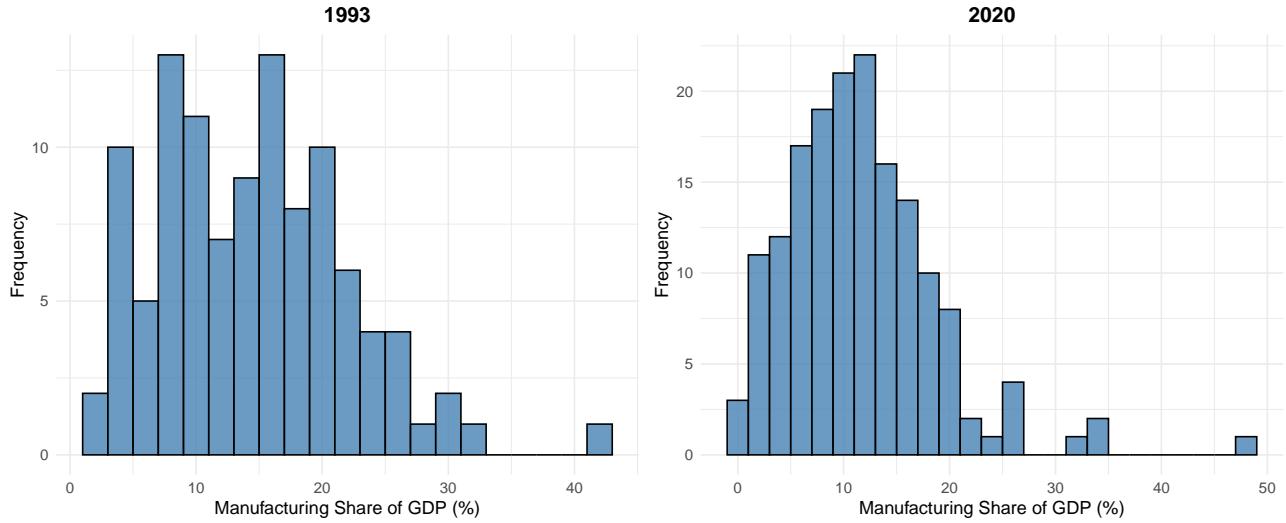


Figure 4: Comparison of the distribution of manufacturing share of GDP in 1993 and 2020.

3.4 Population

Population trends provide essential context for understanding economic activity and night-time light (NTL) intensity patterns. In Figure 5, the total world population is shown to have grown steadily from approximately 4 billion in 1992 to over 7.5 billion by 2020. Figure 6 provides a regional breakdown of average population across intervals, categorized by UN-defined SDG regions. It reveals that regions like Central and Southern Asia and Eastern and South-Eastern Asia consistently have the highest average populations, while regions like Oceania and Sub-Saharan Africa have significantly lower averages. This demographic variation is critical for analyzing NTL because densely populated regions are likely to exhibit higher light intensity due to concentrated urbanization and industrial activity. Conversely, less populated or sparsely developed regions are expected to have lower NTL levels.

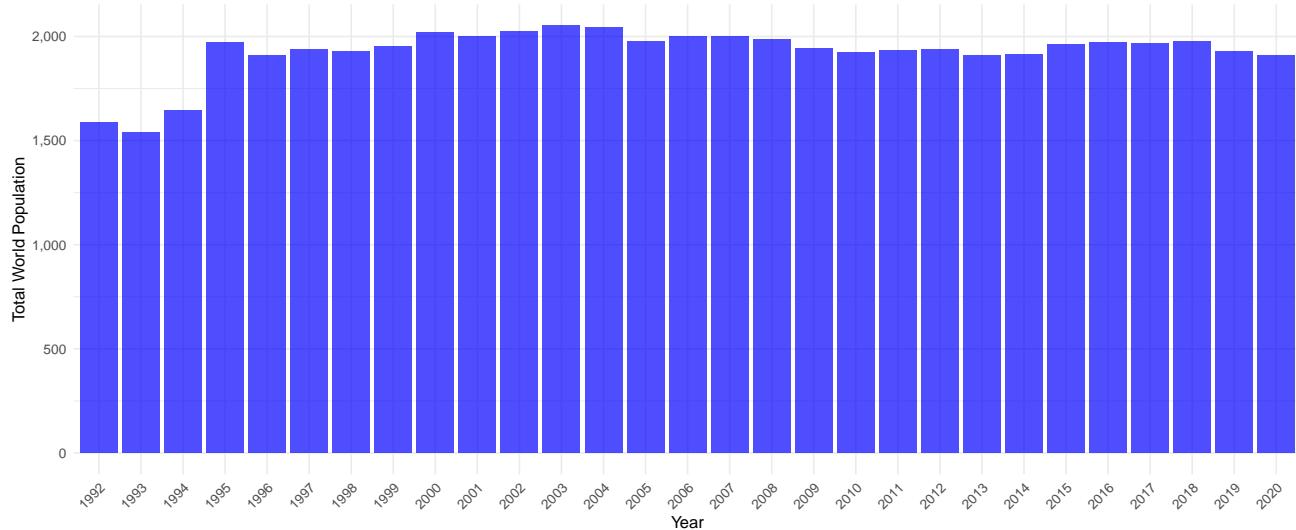


Figure 5: Steady growth of the global population from 1992 to 2020

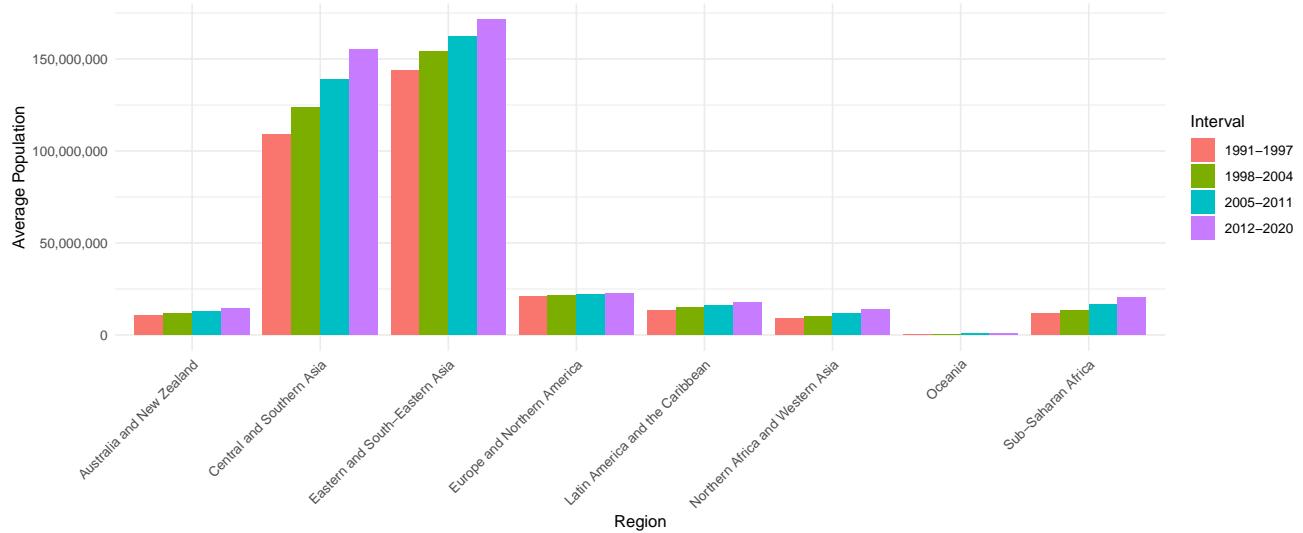


Figure 6: Average population (log scale) across regions for different time intervals (1991–1997, 1998–2004, 2005–2011, and 2012–2020) showing significant population growth in regions such as Central and Southern Asia, Eastern and South-Eastern Asia, and Sub-Saharan Africa over time, with variations across other regions

4 Relationship Between Variables

4.1 Night lights and GDP

Figure 7 plots the log of DN values against the log of GDP for all countries across 30 years, capturing the relationship between night-time light intensity and economic activity. The scatterplot shows a clear positive correlation, indicating that higher GDP values are generally associated with higher DN values.

In Figure 8, we observe how this relationship between DN and GDP varies across countries with different statistical capacities. A list of countries categorized by their statistical capacity grades is given in Figure 12 of the appendix. Countries with higher statistical capacity (graded A and B) exhibit a more tightly clustered and linear relationship. Conversely, countries with lower statistical capacity (graded D and F) show more scatter and variability, suggesting potential discrepancies or weaker data reliability in their national accounts. This shows the intuitive idea that the strength of the DN-GDP relationship can serve as an indicator of the reliability of a country’s national statistical systems.

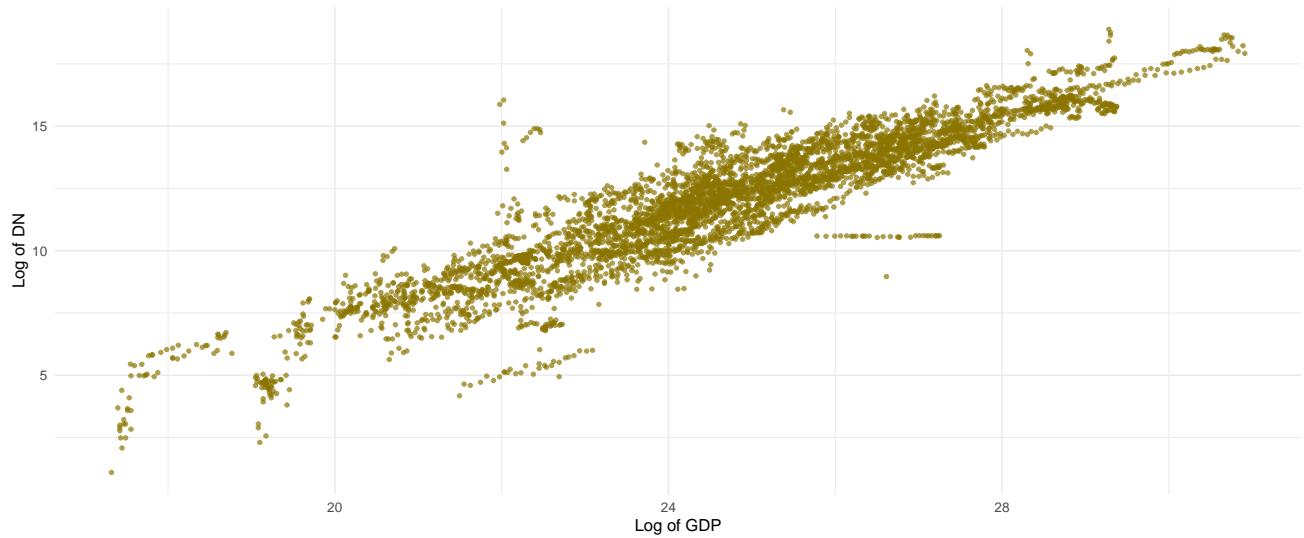


Figure 7: Strong positive correlation between night-time light intensity (Log DN) and GDP (Log GDP), indicating regions with higher GDP levels tend to emit more night-time light

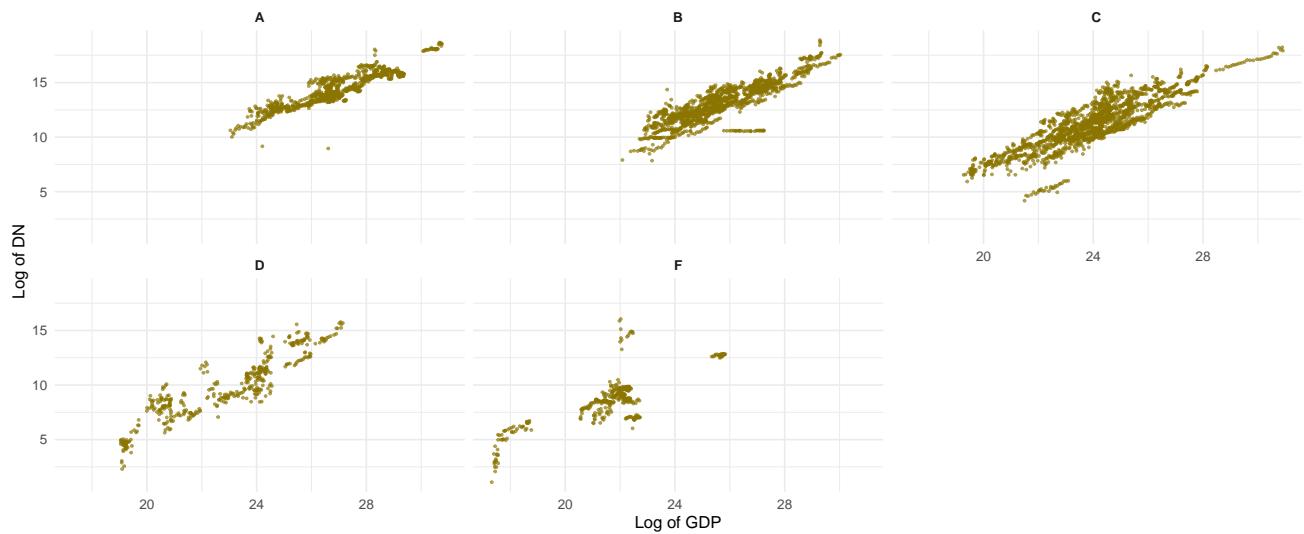


Figure 8: Strength of the correlation between Log DN and Log GDP varies with statistical capacity grades; countries with higher grades (A, B, C) exhibit stronger and more consistent relationships, while lower grades (D, F) show weaker and more dispersed patterns, suggesting the quality of national accounts impacts the NTL-GDP relationship.

4.2 Night lights and Population

Larger populations naturally result in higher night-time light emissions due to increased urbanization and economic activity. Figure 1 confirms this with a clear positive relationship between population (log-transformed) and night-time light intensity (Log DN), highlighting how population size contributes to observable brightness from space.

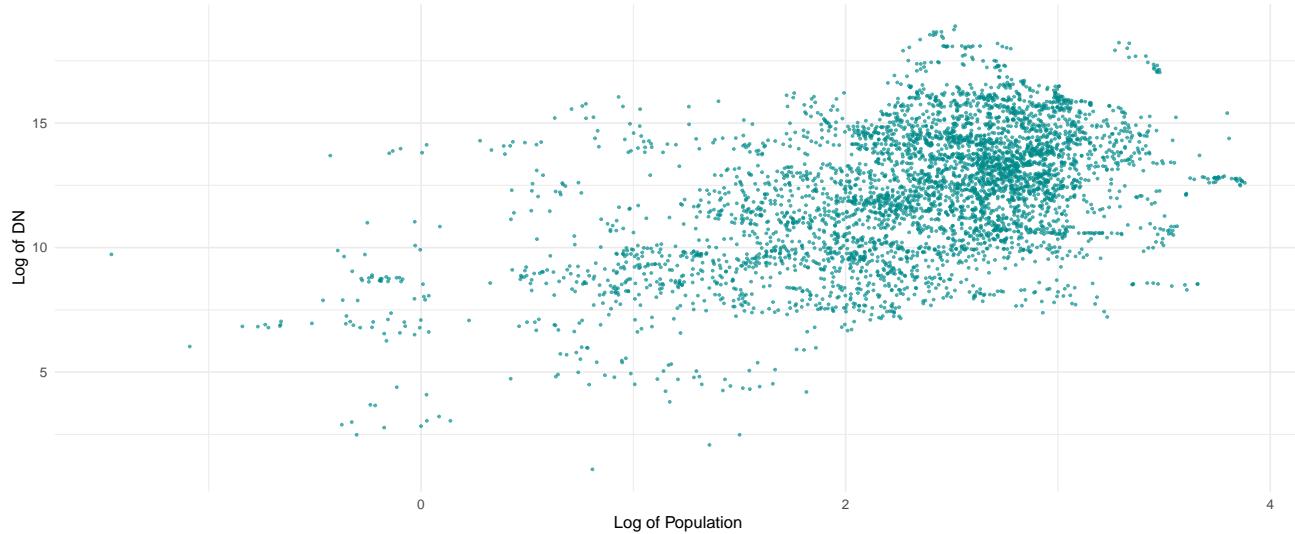


Figure 9: Scatterplot of Population versus DN.

4.3 NTL and Manufacturing Share of GDP

Figure 10 shows the relationship between the manufacturing share of GDP and night-time light intensity. The plot shows a weak positive trend for countries with moderate manufacturing shares (up to 20%), where higher manufacturing activity corresponds to slightly higher DN values. However, the relationship becomes less defined for countries with very high or very low manufacturing shares. This indicates that while manufacturing contributes to night-time light, it is not the sole determinant, and its impact may vary across different contexts.

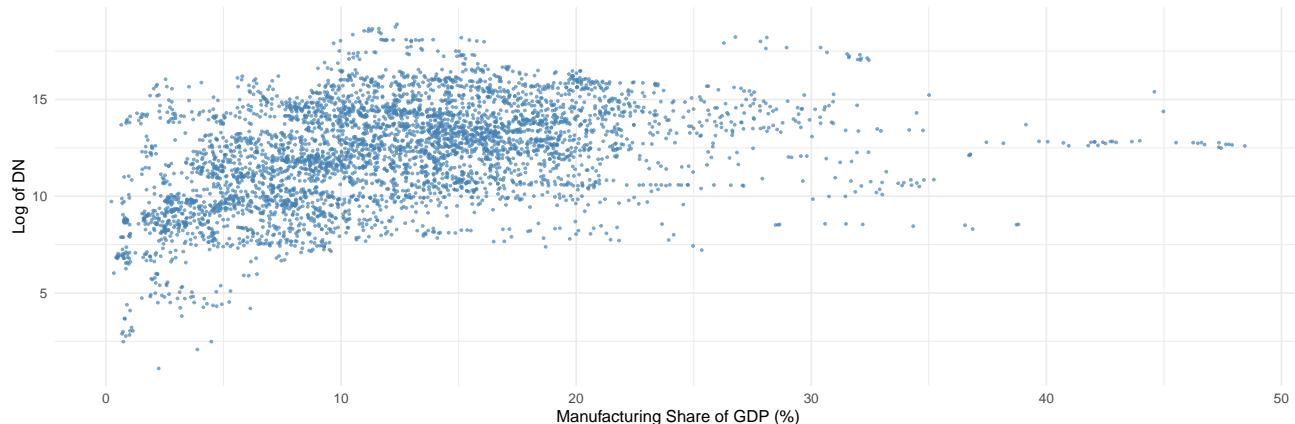


Figure 10: Scatterplot of Manufacturing Share of GDP versus DN.

5 Linear Models

In this section, we present four models to assess the relationship between Night-Time Light (NTL) intensity and various economic indicators, with a particular focus on understanding how NTL correlates with GDP and how this relationship varies across countries with differing levels of statistical capacity. A key challenge in our analysis was the high correlation between GDP, manufacturing share of GDP, and population, as highlighted in the correlation matrix provided in the appendix. This multicollinearity made it impractical to include these variables in the same model without risking inflated standard errors and unreliable coefficients. To address this, we developed separate models for each variable.

The first model examines the relationship between NTL intensity and GDP, incorporating country-specific and year-specific fixed effects. The inclusion of country-specific fixed effects accounts for unobserved factors that differ across countries, such as geographic characteristics, governance structures, or cultural differences. Year-specific fixed effects are included to capture variations over time, such as global economic trends or technological advancements, that may affect the relationship between NTL and GDP.

$$\log(DN_{i,t}) = \beta_0 + \beta_1 \log(GDP_{i,t}) + \alpha_i + \gamma_t + \epsilon_{i,t}$$

- Where:
 - α_i : Country fixed effects
 - γ_t : Year fixed effects

Building on the first model, the second model investigates how the relationship between NTL and GDP varies across countries with differing statistical capacities. As seen in Figure 1, the scatterplot of GDP and NTL faceted by statistical capacity suggests a weaker correlation in countries with lower statistical capacity. To explore this further, we include an interaction term between GDP and statistical capacity grade, allowing us to examine whether countries with stronger statistical systems exhibit a more consistent relationship between NTL and GDP. The intuition is that higher statistical capacity is associated with better data quality and more stable economic structures, which may enhance the reliability of NTL as a proxy for economic activity. Similar to the first model, we control for year-specific and country-specific fixed effects to account for temporal and cross-country heterogeneity.

$$\log(DN_{i,t}) = \beta_0 + \beta_1 \log(GDP_{i,t}) + \beta_2(\text{Grade}_i) + \beta_3(\log(GDP_{i,t}) \times \text{Grade}_i) + \gamma_t + \epsilon_{i,t}$$

- Where:
 - Interaction term:
 $\log(\text{GDP}) \times \text{Grade}$
 - γ_t : Year fixed effects

The third model examines the relationship between NTL intensity and population, while controlling for country and year fixed effects. Population is a key driver of light emissions, particularly in urban areas, and this model isolates its unique contribution to NTL by excluding GDP to address multicollinearity. This approach helps assess whether NTL can serve as a proxy for population, especially in regions where population data may be less reliable, while still accounting for variations across countries and years.

$$\log(DN_{i,t}) = \beta_0 + \beta_1 \log(Population_{i,t}) + \alpha_i + \gamma_t + \epsilon_{i,t}$$

- Where:
 - α_i : Country fixed effects
 - γ_t : Year fixed effects

The fourth model examines the relationship between NTL intensity and the manufacturing share of GDP, controlling for country and year fixed effects. Manufacturing activity, often concentrated in industrial areas, significantly influences light emissions. By isolating this variable, the model highlights how industrialization shapes NTL patterns, independent of overall GDP, while accounting for country- and time-specific factors.

$$\log(DN_{i,t}) = \beta_0 + \beta_1 \text{Manufacturing Share}_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

- Where:
 - α_i : Country fixed effects
 - γ_t : Year fixed effects

6 Model Summary and Results

	(1)	(2)	(3)	(4)
(Intercept)	-12.559 (1.017)	-13.509 (0.200)	10.935 (0.173)	10.983 (0.156)
log(gdp)	0.974 (0.042)			
log(gdp) × gradeA		1.022 (0.007)		
log(gdp) × gradeB			1.021 (0.007)	
log(gdp) × gradeC				1.016 (0.008)
log(gdp) × gradeD				1.003 (0.008)
log(gdp) × gradeF				1.007 (0.009)
log(population)			0.124 (0.034)	
manufacturingsharegdp				0.018 (0.003)
R2	0.958	0.875	0.949	0.950
R2 Adj.	0.956	0.874	0.947	0.947
Num.Obs.	4967	4967	4466	4466

Figure 11: Model Summary of Regre

All models were fit using the built-in `lm` function in R (R Core Team 2024). In the first model, we examine the relationship between Night-Time Light (NTL) intensity and GDP, controlling for country and year-specific fixed effects. The coefficient for $\log(\text{GDP})$ is positive and significant (0.974), indicating that a 1% increase in GDP corresponds to an approximately 0.97% increase in NTL intensity on average. The R^2 value of 0.958 suggests that the model explains 95.8% of the variation in NTL, highlighting a strong relationship. The inclusion of fixed effects ensures that unobserved heterogeneity, such as geographic or temporal factors, is accounted for.

The second model builds on this by including an interaction between GDP and statistical capacity (grade) to explore whether the NTL-GDP relationship varies across countries with differing statistical capacities. While the interaction terms reveal some variation, the results do not fully align with scatterplot observations, which suggested a weaker correlation for lower-grade countries. This raises a methodological question: does it make more sense to analyze the data by running separate regressions for each grade? In Table 3 we will look at the results of the regression when subseted by grades. We will further evaluate the appropriateness of these models in the model diagnostics section, where we will assess and compare their specifications.

In the third model, we replace GDP with population as the primary explanatory variable, again controlling for fixed effects. The positive coefficient for $\log(\text{population})$ (0.124) suggests that a 1% increase in population corresponds to a 0.12% increase in NTL intensity. The R^2 value of 0.949 indicates that population is a significant predictor of NTL, albeit less dominant than GDP.

Finally, the fourth model focuses on the relationship between NTL and the manufacturing share of GDP. The coefficient for manufacturing share (0.018) shows that a 1% increase in this variable is associated with a modest 0.018% increase in NTL intensity. The R^2 value of 0.950 reflects a strong fit, similar

Table 3

	(1)	(2)	(3)	(4)	(5)
(Intercept)	-14.679	-15.596	-13.489	0.765	-6.708
	(2.271)	(1.770)	(1.607)	(2.015)	(7.719)
log(gdp)	1.091	1.124	1.003	0.375	0.723
	(0.097)	(0.075)	(0.066)	(0.087)	(0.352)
R2	0.949	0.954	0.949	0.961	0.837
R2 Adj.	0.946	0.952	0.947	0.957	0.817
Num.Obs.	927	1382	1819	443	396

Model Summary of Regression Subset by Grades

to the population model. This result aligns with the expectation that industrial activity significantly contributes to NTL due to the concentrated energy usage in manufacturing hubs.

This table presents the regression results for the relationship between NTL intensity $\log(DN)$ and $\log(GDP)$ for different subsets of countries based on their statistical capacity grades (A, B, C, D, F). The coefficients of $\log(GDP)$ vary significantly across grades. For Grade A countries, the coefficient is 1.091, suggesting a strong, positive relationship between NTL and GDP. The relationship remains strong for Grade B (1.124) and Grade C (1.003) but weakens notably for Grade D (0.375) and Grade F (0.723). This pattern aligns with the scatterplot observation that the correlation is weaker in countries with lower statistical capacity.

The R^2 values indicate a high explanatory power for all grades, with the highest for Grade D (0.961), potentially due to the smaller sample size. However, the results differ substantially from the interaction model, where the coefficients for $\log(GDP)$ across grades appeared less varied. This discrepancy could arise from multicollinearity or the inability of interaction terms to fully capture grade-specific effects. Further model diagnostics, including multicollinearity checks and goodness-of-fit measures, are required to determine whether separate models or interaction terms provide a better representation of the data.

7 Discussion

Since the availability of NTL data, researchers have discovered diverse applications across economic, social, and environmental domains. NTL imagery serves as a critical proxy for measuring economic activity, particularly in countries where traditional statistics are unreliable or unavailable. For instance, Henderson, Storeygard, and Weil demonstrated how NTL data could adjust GDP growth estimates for countries with weak statistical systems, emphasizing its utility in refining existing economic metrics Henderson, Storeygard, and Weil (2012). Similarly, Chen and Nordhaus (2011) applied NTL data to recalibrate GDP per capita estimates, showcasing its value in complementing conventional economic data Chen and Nordhaus (2011). In many cases, particularly under authoritarian regimes, GDP estimates are often significantly inflated, distorting the perception of economic performance. Such inaccuracies can lead to misguided policy decisions and resource allocations, further exacerbating economic disparities and inefficiencies. Beyond macroeconomic analyses, NTL data have been instrumental in sub-national studies. For example, researchers have used NTL to map urban expansion, track population density, and assess regional inequalities. Studies such as those by Singhal et al. employed NTL data to estimate district-level income and socio-economic indicators, highlighting the potential of this tool for localized economic insights. Singhal, Tarp, and McMillan (2018) Additionally, NTL data have been pivotal in capturing regional variations in infrastructure development and energy consumption, providing a novel perspective on urbanization trends Zhou, Ma, and Zhou (2018).

Despite its numerous advantages, the use of NTL data faces significant challenges. A primary limitation is the temporal inconsistency and calibration issues associated with DMSP-OLS data. The lack of onboard calibration and sensor degradation introduces noise, complicating year-to-year comparisons. Furthermore, DMSP-OLS data suffer from saturation effects in highly illuminated urban areas and blooming effects in suburban and rural regions, leading to under- or overestimation of activity in these zones. The newer VIIRS dataset mitigates some of these issues with higher resolution and improved calibration but lacks the long historical coverage of DMSP-OLS, making it challenging to study trends over extended periods. Zhao et al. (2019) Additionally, variations in lighting intensity are influenced by factors unrelated to economic activity, such as atmospheric conditions, seasonal variations, and cultural practices, which can distort analyses. Another critical limitation is the inability to distinguish between different light sources, such as residential, industrial, or recreational lighting, reducing the specificity of NTL as a proxy for economic activities. Lastly, while combining NTL with ancillary datasets, such as NDVI or land surface temperature, improves its accuracy, it requires significant computational resources and modeling techniques. Addressing these limitations through improved calibration methods, cross-sensor integration, and the development of new algorithms is essential for maximizing the utility of NTL data in future research.

Reassessing the correlation between Night-Time Light (NTL) intensity and GDP is essential as advancements in satellite imaging and extended datasets offer new opportunities to refine our understanding. This study addresses a critical gap by leveraging more recent and comprehensive data to explore how the relationship between NTL and economic activity holds up across varying statistical contexts. With the increasing importance of alternative economic proxies, especially in regions where traditional metrics may be unreliable, understanding the nuances of this correlation has both academic and policy implications.

The findings reaffirm the usefulness of NTL as a proxy for GDP, reflecting its capacity to capture broad patterns of economic activity. However, the variation in correlation strength across countries with different statistical capacities underscores the complexity of relying on NTL data universally. In countries with weaker statistical systems, the weaker correlation suggests potential inconsistencies in how NTL relates to economic structures or data quality issues in the official GDP figures. This highlights

the dual role of NTL as both a complement to and a critique of traditional economic metrics. For policymakers, these insights emphasize the need to treat NTL as a supplementary tool rather than a standalone measure.

While this study provides a valuable perspective, it also raises questions about the best methods to analyze the relationship between NTL and GDP in varied statistical contexts. The dual approach—using both interaction terms and subset regressions—offers insights but leaves open the question of which method better captures the nuances of statistical capacity differences. A deeper investigation into model selection, diagnostics, and validation is necessary to establish a framework that balances parsimony with explanatory power. Future research could explore alternative modeling strategies, such as mixed-effects models or machine learning approaches, to better capture the non-linearities and contextual differences that may underlie the observed variations.

Another avenue for future exploration lies in understanding how other variables, such as energy efficiency improvements, lighting technologies, and policy changes, influence the NTL-GDP relationship over time. The role of urbanization and industrialization, both key drivers of NTL, also warrants a more detailed examination, particularly in rapidly developing regions where structural changes are likely to alter the nature of this correlation. Incorporating spatial data and finer-resolution imagery could further refine our understanding, enabling a more localized assessment of economic activity.

8 Appendix

8.1 Countries Grouped By Statistical Capacity

Grade	Countries
A	Armenia, Australia, Austria, Canada, Chile, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovenia, Spain, Sweden, Switzerland, Turkiye, United Kingdom, United States
B	Albania, Argentina, Azerbaijan, Belarus, Belgium, Bolivia, Brazil, Bulgaria, Colombia, Costa Rica, Croatia, Cyprus, Dominican Republic, Ecuador, El Salvador, Ghana, Guatemala, Iceland, India, Indonesia, Kazakhstan, Luxembourg, Malaysia, Malta, Mauritius, Moldova, Mongolia, Montenegro, Morocco, North Macedonia, Pakistan, Paraguay, Peru, Philippines, Romania, Russian Federation, Rwanda, Senegal, Serbia, Singapore, South Africa, Sri Lanka, Tanzania, Thailand, Tunisia, Uganda, Ukraine, Uruguay
C	Afghanistan, Algeria, Angola, Antigua and Barbuda, Bahrain, Bangladesh, Belize, Benin, Bhutan, Bosnia and Herzegovina, Botswana, Brunei Darussalam, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, China, Cote d'Ivoire, Eswatini, Ethiopia, Fiji, Guinea, Guyana, Honduras, Jamaica, Jordan, Kenya, Kuwait, Lebanon, Lesotho, Liberia, Madagascar, Malawi, Maldives, Mali, Mauritania, Mozambique, Myanmar, Namibia, Nepal, Nicaragua, Niger, Nigeria, Oman, Palau, Panama, Qatar, Samoa, Sao Tome and Principe, Saudi Arabia, Seychelles, Sierra Leone, Suriname, Tajikistan, Timor-Leste, Togo, Tonga, Trinidad and Tobago, United Arab Emirates, Uzbekistan, Zambia, Zimbabwe
D	Chad, Djibouti, Dominica, Equatorial Guinea, Gabon, Guinea-Bissau, Haiti, Iraq, Kiribati, Libya, Marshall Islands, Papua New Guinea, Solomon Islands, Somalia, South Sudan, Sudan, Turkmenistan, Vanuatu
F	American Samoa, Andorra, Aruba, Barbados, Bermuda, British Virgin Islands, Cayman Islands, Central African Republic, Comoros, Cuba, Curacao, Eritrea, Faroe Islands, French Polynesia, Gibraltar, Greenland, Grenada, Guam, Isle of Man, Liechtenstein, Monaco, Nauru, New Caledonia, Northern Mariana Islands, Puerto Rico, San Marino, Turks and Caicos Islands, Tuvalu

Figure 12: List of Countries Grouped by Grade.

8.2 Correlation Between Variables

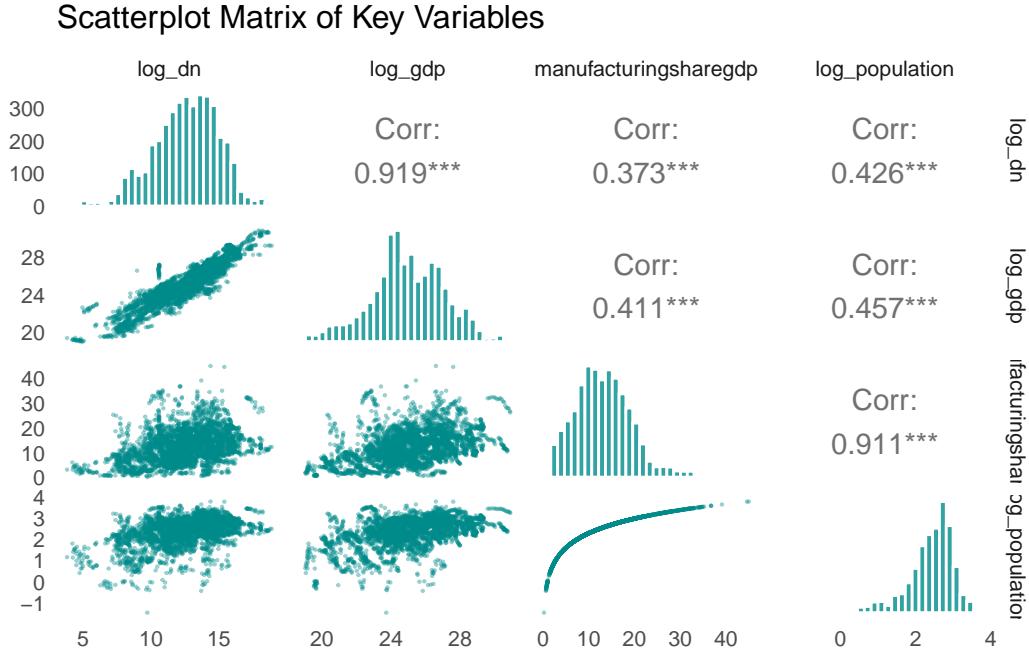


Figure 13: Scatterplot matrix showing pairwise relationships between key variables in the analysis_data dataset.

8.3 Model Diagnostics

Overall, the diagnostics across all models suggest a reasonable fit, with residuals generally well-distributed around zero, indicating good adherence to linear model assumptions. For Model 1, as shown in Figure 14 the residuals show minimal patterns, supporting the model's adequacy, while the Q-Q plot confirms approximate normality with only minor tail deviations. The Scale-Location plot indicates consistent variance, and although some high-leverage points are identified, none seem overly influential. Similarly, Model 2 as shown in Figure 14 maintains an even spread of residuals, and its Q-Q plot shows a good fit to normality, with minor deviations in the tails. High-leverage points in Model 2 are slightly more pronounced, with one exceeding Cook's Distance threshold, but the model remains stable overall.

For Model 3, as shown in Figure 15 the diagnostics indicate a well-fitting model with residuals showing no major patterns and Q-Q plots closely following normality. While residual variance is largely consistent, some variability is noted at higher fitted values. High-leverage points align with those observed in earlier models but do not excessively influence the results. Model 4, as shown in Figure 15 demonstrates an acceptable fit overall, though it exhibits slightly more tail deviation in the Q-Q plot compared to the other models. The Scale-Location plot and Residuals vs. Leverage plot suggest minor issues with variability and high-leverage points, respectively, but these remain within tolerable limits.

The subset models provide insights into the relationship between GDP and NTL by estimating separate regressions for each statistical capacity grade. For grades A, B, and C, the Residuals vs. Fitted plots demonstrate that the residuals are evenly distributed around zero, supporting the linear model assumption as seen in Figure 16 and Figure 17. Grades D and F, however, exhibit heteroskedasticity,

with residual variance increasing at higher fitted values. This indicates that the model does not fully capture the variability in NTL for countries with lower statistical capacity.

Q-Q plots show that residuals for grades A, B, and C adhere to normality, with only minor deviations. For grades D and F, however, there are pronounced departures in the tails, suggesting skewness or outliers. The Scale-Location plots confirm these findings, with grades D and F showing distinct heteroskedasticity. Residuals vs. Leverage plots highlight high-leverage points in all subsets, particularly for grades D and F, where countries with extreme GDP or NTL values influence the model. These findings suggest that models for countries with lower statistical capacity may require adjustments, such as robust standard errors or alternative specifications.

When evaluating which model is better for assessing country-specific grades, Model 2 provides a unified framework by incorporating an interaction term between GDP and statistical capacity grade. This allows for generalizing the relationship between GDP and NTL across all grades within a single model. However, diagnostics reveal that this approach may oversimplify the heterogeneity across grades, particularly for countries with lower statistical capacity, as it assumes that the interaction term sufficiently captures all differences. In contrast, the subset models, which estimate separate regressions for each grade, highlight distinct patterns in residual variance and normality for grades D and F. These patterns are not adequately addressed by Model 2, suggesting that the subset approach may provide more accurate insights for understanding the dynamics specific to each grade. Thus, while Model 2 is better suited for examining overarching trends across grades, the subset models offer a better understanding of country-specific grade differences.

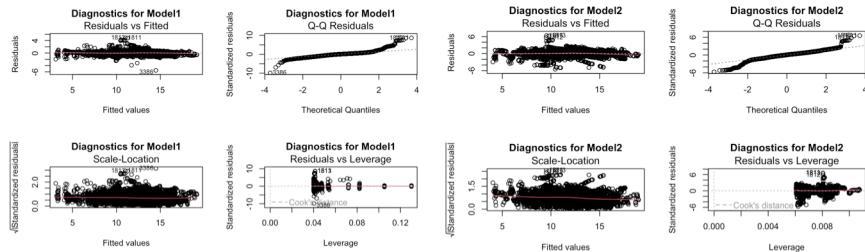


Figure 14: Diagnostic Plots for Model 1 and 2

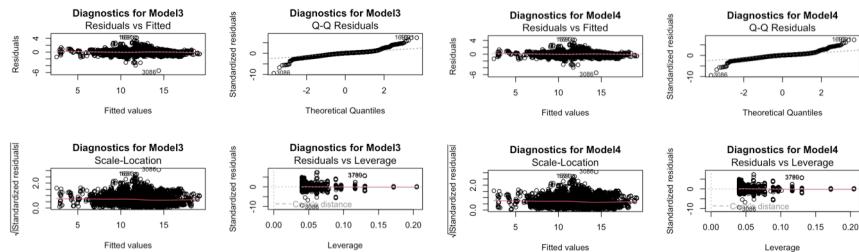


Figure 15: Diagnostic Plots for Model 3 and 4

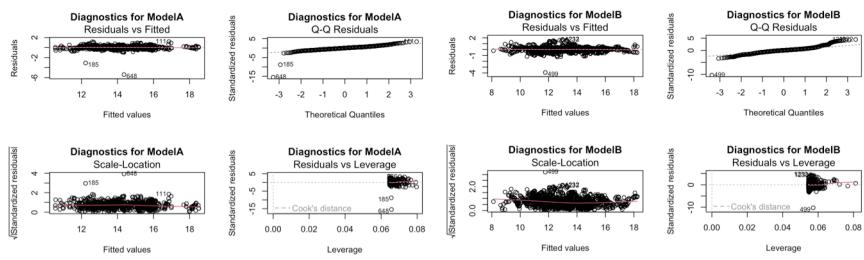


Figure 16: Diagnostic Plots for Model 5 and 6

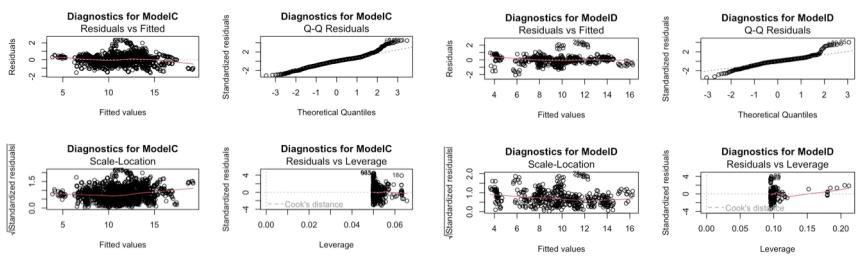


Figure 17: Diagnostic Plots for Model 6 and 7

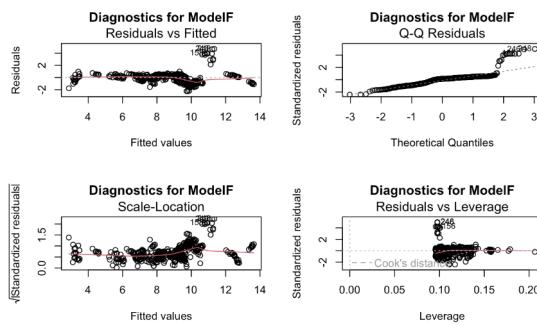


Figure 18: Diagnostic Plots for Model9

9 Understanding Satellite-Derived NTL Data and Measurement

9.1 Raster Data

Raster data is a spatial data format that represents geographic information as a grid of cells or pixels, each with an associated value. These values can represent various phenomena, such as elevation, land cover, or light intensity. The resolution of raster data is defined by the size of each cell, with smaller cells offering finer detail. Each cell corresponds to a specific geographic area, and the value stored in it reflects a measurement or observation of that area. Raster data is commonly used in remote sensing and Geographic Information Systems (GIS) due to its compatibility with satellite imagery and other gridded datasets. It is widely used for analyzing patterns, modeling spatial phenomena, and visualizing geographic features.

9.2 NTL as Raster Data

Night-Time Light (NTL) data is a specific form of raster data, collected from satellite observations that measure the intensity of artificial light emitted at night. This data is often represented in grid cells, with a typical resolution expressed in geographic units such as arc-seconds (1/3600th of a degree). Each cell in the NTL raster represents the intensity of light detected over a specific area, with higher values indicating brighter regions. NTL data typically uses dynamic radiometric calibration to adjust for atmospheric interference and sensor degradation, ensuring consistency over time. The datasets commonly used include those from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) and the Visible Infrared Imaging Radiometer Suite (VIIRS). These datasets are crucial for creating a spatially explicit representation of human activity and infrastructure.

9.3 How Activities Translate into NTL

NTL data captures a range of human activities, making it a valuable proxy for economic and social indicators. Urbanization results in bright city lights, which dominate NTL intensity in developed areas. Industrial activities contribute heavily to light emissions from factories, ports, and transport networks. Rural electrification, often reflected in lower-intensity but widespread lighting, can indicate socioeconomic development. Conversely, areas with dim or no light often signify regions lacking infrastructure or experiencing economic stagnation. Seasonal activities, such as agricultural harvests, and transient phenomena, like large gatherings or festivals, also contribute to variations in light intensity. However, the relationship between these activities and NTL is not linear; for example, bright urban centers often experience “saturation,” where NTL values fail to capture variations in economic intensity accurately.

9.4 Topcoding and Its Challenges

Topcoding is a process used to cap the maximum values in raster datasets, including NTL data, to prevent saturation effects. For instance, in urban centers with extremely high light intensity, raw NTL values may reach the sensor's maximum detection threshold, leading to a loss of granularity. While topcoding ensures data usability and consistency, it introduces challenges in accurately interpreting highly urbanized areas. It underestimates the variability and economic intensity of these regions, biasing analyses that depend on precise measurements of light intensity. Alternative approaches, such as using VIIRS data with a wider dynamic range or integrating ancillary datasets like land cover or economic

statistics, are employed to mitigate these effects. However, these methods also have limitations, such as added complexity and reliance on external datasets.

9.5 Advances and Future Directions

Advancements in satellite technology, such as onboard calibration systems and higher radiometric resolution, are reducing traditional limitations of NTL datasets. Modern sensors like VIIRS provide finer spatial and temporal resolutions, enabling more accurate monitoring of human activities. Integration of NTL data with other geospatial datasets, such as socio-demographic statistics, enhances its utility for interdisciplinary research. Future research could focus on developing methods to harmonize long-term datasets from multiple sensors, addressing issues like temporal inconsistency and cross-sensor calibration. Additionally, exploring machine learning techniques for extracting patterns from NTL data could offer new insights into urbanization, development, and disaster response. These advancements hold the promise of making NTL data even more reliable for understanding global socioeconomic dynamics.

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