CORRELATION OF NIGHTTIME LIGHTS AND ECONOMIC INDICATORS IN SRI LANKA

JULY 2025

ADVOCATA

Correlation of nighttime lights and economic indicators in Sri Lanka

Correlation of nighttime lights and economic indicators in Sri Lanka

Janani Wanigaratne 1** , Thashikala Mendis 1** , Charith Peris *
* This work does not relate to author's role at Amazon.
** The opinions expressed in this article are the authors' own and do not reflect the view of the institutions they are currently affiliated with.
1 Contributed Equally

Abstract

Economic and poverty indicators collected via surveys can have long lag times before they are available for policy consumption. In developing and least developed countries, these surveys are also sparsely conducted. Studies have shown that nighttime light (NTL) data might be usable as a proxy for certain economic indicators. NTL is available daily, and is obtainable at a very low cost. Therefore, for countries like Sri Lanka with poor and infrequent data collection, NTL can be a resource of value for gauging economic growth and development. In this work, we explore NTL correlation to economic variables, specifically employment rate and poverty, at district level and at Grama Niladhari Division [1](GND) level. We present observations on the possible use of NTL as a supporting variable for the calculation of poverty in Sri Lanka.

[1] Smallest administrative unit in Sri Lanka.

1. Introduction

One of the main reasons for the growing popularity in using nighttime lights (NTL; see example in Figure 1) to bolster economic indicator measurement is its availability. Economic indicators collected via surveys can have a lag time of several years (European Commission 2023) before it is available for analysis and decision making. In contrast, updated NTL data is available daily, and is obtainable at a very low cost. Therefore, when it comes to developing and least developed countries, where poor and infrequent data collection has been an added constraint, NTL can be a resource of value for gauging economic growth and development.

The goal of this study is to identify correlations between NTL and poverty (tracked via the use of employment rate and poverty headcount in Sri Lanka, to identify ways in which nightlights can be used to extract information on poverty in regions where indicator data is scarce. We present our study as two phases.

Phase 1: NTL correlation to employment rate and poverty at district level: The results of this phase provides insight into correlations at a macro-level. For this phase, we have robust economic indicator data, but we expect low actionability.

Phase 2: NTL correlation to employment rate and poverty at Grama Niladhari Division[2] (GND) level: The results of this phase provide insight into correlations at a micro-level. However, the only available official data for GND level is on employment for 2012 and therefore we encounter limitations on the timeliness of the findings.

Our contributions are as follows:

1. We present our findings on how NTL maps to employment rate and poverty at district level, and the information that we can obtain from these correlations.
2. We present our preliminary findings on how NTL maps to employment rate at GND level.
3. We present our observations on the possible use of NTL as a supporting variable for the calculation of poverty in Sri Lanka.

[2] Smallest administrative unit in Sri Lanka.

2. Related work

2.1 The use of NTL as a proxy for economic activity

The United States Air Force's Defense Meteorological Satellite Program (DMSP) has been collecting NTL data since the 1970s using Operational Linescan System (OLS) sensors. Originally designed for detecting moonlit clouds, these sensors also capture human-made lights. The data, processed by National Oceanic and Atmospheric Administration's (NOAA) National Geophysical Data Center, excludes natural light sources like the light from the bright half of the lunar cycle, auroras, and forest fires (Henderson, Storeygard, and Weil 2012). A post-processed version of these datasets of nighttime lights are made publicly available and enable researchers to study global human activity and settlement patterns.

The use of NTL imagery to detect economic activity instead of traditional economic data has become increasingly popular in the past few decades. This method uses the satellite images that capture night time light emissions from a particular area to gain insights into its economic activity. The core rationale behind this method is the assumption that areas with higher light emission (radiance and higher intensity) tend to have a higher level of economic activity in contrast to an area with less light emission. Using this as a basis, studies like (Henderson, Storeygard, and Weil 2012) showed that NTL data becomes a useful proxy for economic activity at both temporal and geographic scales in cases where traditional data are of poor quality or are unavailable.

NTL provides objective data as well as rigorous coverage since they are collected through satellites. As a result, analysis into a wide range of research areas has been revolutionized, especially in the case of remote regions and locations where official survey-based data is not available. For instance, (Eun and Skakun 2022) uses NTL to detect the change in land use that ensued from the military conflict in Eastern Ukraine. Similarly, (Li et al. 2015) uses NTL to detect Northern Iraq insurgency demonstrating how city lighting in different regions changed when seized by ISIS. (Kim 2022) uses NTL as a proxy for Gross Regional Domestic Product (GRDP) to assess the regional economy in North Korea and estimates the GRDP per capita for several counties. It demonstrates how NTL can be used in cases like North Korea with restricted data accessibility especially at regional level to conduct comprehensive economic analyses.

The use of NTL is not limited to such extreme cases. It has been used by both developed and developing countries alike. (Townsend and Bruce 2010) uses NTL to develop a map of Australian electricity consumption with respect to population statistics while (Xie and Liu 2018) uses NTL to validate the use of geocoded address databases for mapping urban extent and its potential to monitor and model urban growth and change.

However, seemingly NTL is much more popularly used in developing countries to observe socioeconomic indicators which ensues from the limitations in the existing statistics. One such limitation is that for the existing economic indicator data is collected infrequently, with large time intervals between collection years. For instance, (Subash et al. 2019) uses satellite NTL data to predict poverty in rural India; as the poverty statistics in India are only released once every five years, the econometric modeling that the existing statistics allow is extremely limited. This results in using outdated data in economic modeling and policy measures. As the findings indicate a negative relationship between the NTL and poverty indicators, the paper suggests using NTL to model economic relationships to answer policy questions which have otherwise been constrained by the lack of frequent data. Similarly (Puttanapong et al. 2022) uses geospatial data including NTL to predict the poverty in Thailand. Even though official poverty statistics were produced through Household Socioeconomic Survey, estimates at a granular level required for sound policy implementation are unavailable. Furthermore, delayed reporting and in some cases lack of reliability and transparency of the official poverty statistics encourage substituting them with NTL data, which is available in real time. For instance, (Li et al. 2023) demonstrate how it is more reliable to use NTL data in detecting poverty in a target area in China due to the available data being outdated as inconsistencies caused by administrative changes.

Sri Lanka being a developing country, faces similar constraints in terms of the data on economics indicators (refer to section 4.2 for more details). Despite this lack of official survey data at frequent intervals, the use of NTL to detect poverty or other economic activity is limited. One such study is (Chen, Lu, and Nanayakkara 2021) which explores how Asian Development Bank's rural road connectivity program has impacted the local economic activity in the Southern province using NTL. The lack of reliable sub-national data in high frequency and granularity in Sri Lanka to evaluate the actual impact of the iroad connectivity program has driven the authors to the use of NTL as an alternative. The paper argues for a relationship between NTL and economic indicators such as labor force, population and the number of households with electricity. However, the elasticity (0.2) as well as the R^2 value of the model (16%-17%) indicates a weak correlation. This is attributed by the authors to be due to low population density in Southern province. Similar to using NTL as a proxy for economic activity, remote sensing data has been used in detecting poverty to a certain extent in the existing literature. (Daniele et al. 2018) uses remote sensing data to detect spatial patterns of inequality with the intention of mapping deprived communities and poverty at a regional, national and local scale. (Baud et al. 2010) uses high resolution satellite data to spatially locate and analyse urban poverty in Delhi, highlighting the limitations of citywide statistics that often hide spatial heterogeneity.

3. Poverty in Sri Lanka

3.1 Overview of Poverty in Sri Lanka

Poverty measurements are used to provide invaluable insights into any economy and its performance overall. So in Sri Lanka's case poverty has been extensively studied over time and tells the story of Sri Lankan economy through its many milestones such as the civil war, economic and financial crises, transitioning to an upper middle income country and global pandemics among many others. For instance, poverty rates have declined from 22.7% in 2002 to 6.7% in 2012 indicating the impact of civil war on national poverty figures (Ranawana 2018). According to The Centre for Poverty Analysis (CEPA) the number of poor people rose from 2.5 million in 2019 to 5.7 million in 2022, as a result of the Covid 19 pandemic (Abeyratne 2024). (The World Bank 2021) states that the progress made through poverty alleviation and development measures since around 2016 was reversed by the pandemic. Additional to the changes in poverty measures influenced by such events over time, distinctions in poverty at a cross sectional level can also be seen. These disparities are observed among regions as well as communities. According to (Sakalasooriya 2021), points out the poverty gap between the rural and urban population that has persisted through decades despite the decline in overall poverty figures, highlighting the insufficient change in rural economies, and the significant disparities in development approaches between rural and urban sectors. The author also highlights the regional disparities in poverty that stem from regional development disparities, referring to how Colombo (0.6%) has the lowest rate of poverty headcount while Mullaitivu (11.2%) and Kilinochchi (15%) have the highest rate of poverty headcount in 2020. On the other hand, poverty levels among the estate sector community in Sri Lanka has been consistently higher than both the rural and urban sectors. Accordingly, even though the national poverty rates have been showing an overall declining trend over time, the regional poverty disparity is still significant (Deyshappriya 2023). Hence, the use of multidimensional poverty measures complementing the traditional monetary poverty measures (the approach used by the Department of Census and Statistics (DCS) to calculate official poverty statistics) is becoming prominent recently (Deepawansa 2023). According to the National Multidimensional Poverty Index (NMPI), estate areas are considered poverty pockets as more than half of the population (51.3%) in such communities are poor while more than eight out of every ten (80.9%) poor people live in rural areas (Department of Census and Statistics and Ministry of Economic Policies and Plan Implementation 2021).

Upon reviewing the existing knowledge about poverty in Sri Lanka it becomes quite clear that poverty takes a dynamic nature across time as well as across regions and communities which require timely and targeted policy measures, and the inadequacy of the existing poverty statistics in supplementing the design and implementation of such policy measures.

3.2 How poverty is calculated in Sri Lanka[3] (see Appendix D for more information)

Poverty statistics in Sri Lanka play a crucial role in understanding the evolution of economic well being of its citizens over time and in implementing appropriately targeted policy measures for poverty alleviation. The Official Poverty Line (OPL) is the key tool on which the official poverty statistics are based upon. The OPL reflects the minimum expenditure incurred per person per month to fulfill basic needs.

Based on the OPL, numerous poverty statistics are derived such as Poverty Headcount Index, poverty gap as well as poverty distribution by sectors, provinces and districts. Among these, poverty headcount index, also known as the poverty rate, refers to the percentage of people that fall below the OPL. Accordingly, any individual whose per capita monthly real expenditure is less than the OPL, is considered poor. The Household Income and Expenditure Survey (HIES) is the main data source for calculating these indices in Sri Lanka, which are conducted every 4 years. Hence, despite being an integral element in policy instruments, data updates are infrequent.

3.3 Using NTL to detect poverty in Sri Lanka

Despite its growing popularity as a proxy for economic activity, NTL is still in its infancy in terms of its use in Sri Lanka. However, Sri Lanka also struggles with multiple constraints such as the unavailability of data at a granular level and high frequency that impedes timely economic analysis and forecasts.

While surveys such as HIES generate reliable and valuable insights into the economy, they are not frequent enough to enable timely economic analysis that would have an impact on policy decisions. At the same time, these surveys do not record data at a granular level, such as Grama Niladhari Division or Divisional Secretariat levels, hence failing to give insights into the poverty evolution in small and remote geographic regions. This eventually leads to policy measures that do not consider such areas.

As a solution to these constraints, NTL can be used in conjunction with the survey data to make timely and targeted policy decisions. According to (Newhouse 2017) such infrequent availability of poverty statistics calls for the use of high resolution satellite imagery to fill this severe gap and supplement HIES data. The article also refers to the significance of poverty maps in Sri Lanka including an instance in which the use of poverty maps in selecting 113 poorest Divisional Secretariats when reforming the Samurdhi transfer program. This perspective is not uncommon, since the use of NTL and satellite imagery in general is regarded as a novel approach that can be used in development settings including poverty measures in data deprived countries like Sri Lanka (Shanmugarajah and Chandana 2020).

[3] DCS Sri Lanka

4. Data

4.1 NTL data

In this work, we use Visible Infrared Imaging Radiometer Suite (VIIRS) Nighttime Light Data, accessed via Google Earth Engine and provided by the Earth Observation Group (EOG).The data includes two versions: the Non-Stray Light Corrected version (2012–2024), which offers better quality compared to DMSP OLS but can be affected by stray light, and the Stray Light Corrected version (2014–2024), which improves data quality, particularly in the polar regions. However, it should be noted that some artifacts may be introduced in twilight regions due to the correction process. Both versions exclude cloud-affected data and temporary light sources, offering reliable insights into global nighttime light patterns and human activity (Appendix A).

4.2 Lack of Data

The predominant driving force behind using NTL as a proxy for economic activity is the lack of data. As discussed in section 2 (Related work) conducting proper timely economic analysis especially in developing countries is severely bounded by their data constraints. For instance, the poverty statistics such as the Poverty Head Count Ratio (PHCR) and Poverty gap in Sri Lanka are calculated based on the HIES which is conducted only once every three years, and it usually takes about a year for the data to be published. As a result, the poverty statistics are also available only for the HIES years. Since statistics on economic indicators are highly integral to timely implementation of policy measures that are appropriately targeted are sparse, such constraints force the policy makers to rely on outdated survey year data until the next survey year arrives, even if the economy goes through severe changes, rendering the policy measures ineffective.

The next biggest concern is the lack of data at a granular level, even for the survey years. For instance in Sri Lanka, the data could only be obtained up to district level. Even though the DCS collects data on GND level through the Census of Population Housing, surveys at such granularity are conducted only every ten years. For this reason, issues like poverty pockets in smaller administrative units such as Grama Niladhari divisions cannot be identified. Hence, targeted and concentrated policy measures remain unfeasible. Moreover, for some indicators like the Gross Domestic Product (GDP), the data could only be obtained up to provincial level. Such severe constraints require a supplement to the official statistics (Newhouse 2017).

(Chen, Lu, and Nanayakkara 2021) calls attention to these limitations when examining the growth in economic activity that resulted from the Asia Development Bank's (ADB) rural road connectivity programme using NTL. According to the paper, drawing comprehensive insights on economic growth resulting from their development programme would require frequent and representative longitudinal socioeconomic data focusing on households, individuals and economic outcomes at micro level geographical units, which are not available in Sri Lanka, particularly at high frequency and granularity. This has compelled the authors to resort to NTL as a proxy for economic activity.

4.3 Economic variables and the rationale for their choice

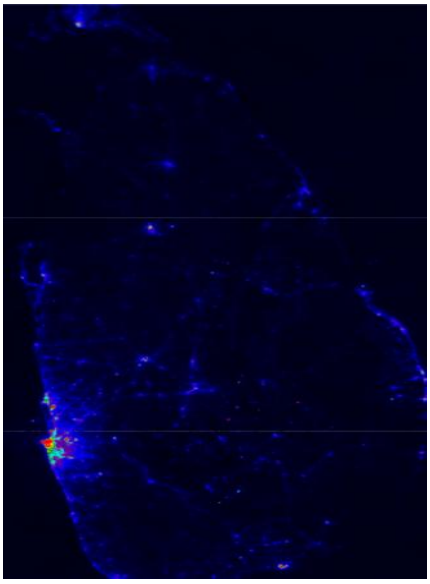
In this study we attempt to detect poverty in Sri Lanka using NTL data. However, as discussed in section 3 poverty statistics are not available at frequent time intervals or at high granularity. Hence, we use an alternative economic indicator, employment rate, in addition to the available poverty statistics to validate the relationship between NTL and poverty.

Labor force statistics are known to be fundamental determinants of poverty. The rationale behind the link between labor force statistics such as employment rate and poverty is that higher employment rate can lead to higher income generation which results in poverty alleviation. (Rammohan and Tohari 2023) demonstrates how labor force participation leads to poverty reduction, evaluating the impact of Indonesia's Village Fund Programme "Dana Desa". The paper concludes that participation in such employment programs have significantly contributed to the reduction of rural poverty. (Stevens and Pihl, 2016) claims that this link between poverty and employment remains the same in developed countries like the USA, by showing that the poverty rates are much higher among the unemployed than among the employed.

5. Results

5.1 Experimental Setup

To process the NTL data, we utilized Google Earth Engine (GEE) to extract and prepare the data for analysis. We filtered the dataset to focus on the specific geographic boundaries of the districts and Grama Niladhari Divisions (GNDs) in Sri Lanka, using the boundaries provided by the Survey Department of Sri Lanka (GIS Branch, Survey Department of Sri Lanka, n.d.). The NTL dataset includes pixel-level measurements for nighttime light intensity (average radiance (avg_rad)) and cloud-free coverage (cf_cvg). For each district and month, we calculate the total nighttime light intensity by summing the avg_rad values of pixels within the district, where pixels are those with cloud-free coverage above 50%. This sum represents the total light intensity for the district during that particular month. Simultaneously, we calculate the average light intensity by dividing the total intensity by the number of valid pixels, providing the mean intensity for each district and month. Once these metrics are obtained for each district and month, we aggregate the data at the yearly level by summing the monthly total intensities to get the yearly total light intensity, and averaging the monthly average intensities to get the yearly mean light intensity. During this process, we assumed that pixels with cloud cover greater than 50% were unreliable and excluded them. Additionally, it was assumed that each month contributed equally to the yearly totals and that missing or excluded data due to cloud cover was randomly distributed, minimizing bias. Also, in the GND analysis, we noticed a few inconsistencies between the GND names in the shapefiles obtained from the Survey Department and the GND names in the Census of Population and Housing. We had to exclude these GNDs from the analysis to ensure consistency in the GND names and to improve accuracy.



Source : Authors' estimate

Figure 1: Night time lights in Sri Lanka in 2023

5.2 NTL correlation to economic variables at district level

5.2.1 NTL correlation to employment rate at district level

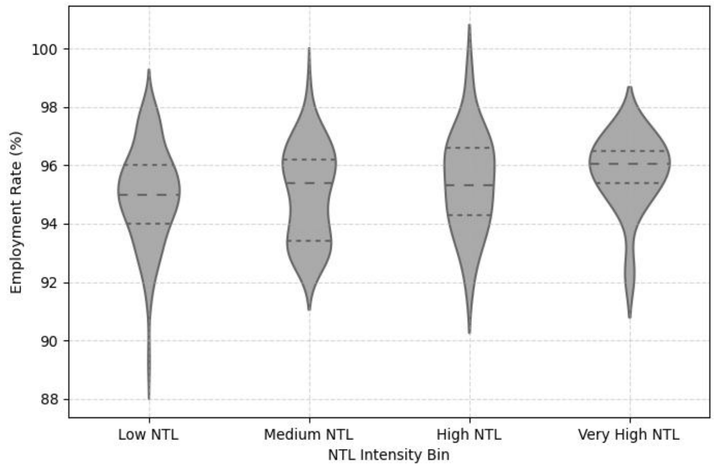
Given the unbinned district level data, NTL versus employment rate was observed to be noisy with no strong correlation observed. As shown in Table 1, we observe that the elasticity of employment rate with respect to NTL is 0.00596 with an R squared value of 5.8%.

Table 1: Elasticity of NTL and Employment

	Coefficient	Standard Error	P value
Intercept	4.51	0.015	0
Employment	0.006	0.002	0.00092
	R squared	Adjusted R squared	Standard Error
	0.06	0.053	0.016

Source : Authors' calculation

We also explored the use of a neural network (architecture and set up details in the Appendix B) to explore the predictability of employment rate given NTL. This was achieved by randomly splitting the dataset into five partitions and using K-fold cross validation to iteratively train a neural network regression model on four of the five partitions and test the fit of the neural network predictions on the held out partition. When this exercise was done, we saw a mean train root mean squared error (RMSE) of 3.56 and a mean test RMSE of 4.73. The higher RMSE values show that the predictability is low, corroborating our low elasticity result in the previous section.

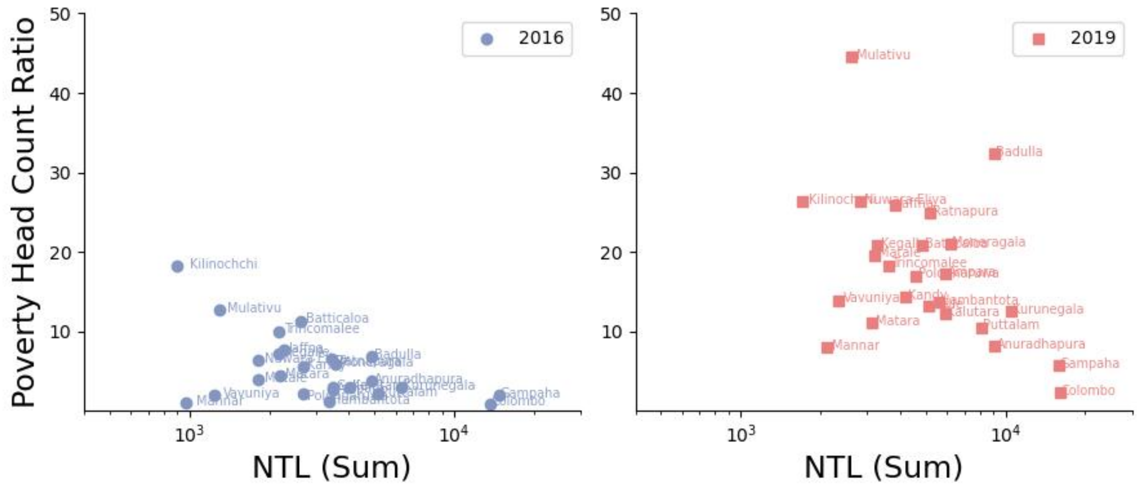


Source: Authors' estimate

Figure 2: Distributions of employment rate within NTL intensity bins Low, Medium, High and Very high.

We then defined bins of NTL intensity of ranges 0-4000, 4000-6000, 6000-8000, and 8000-10000 referring to these as Low, Medium, High and Very high. As shown in Figure 2, these bins enable us to see an increasing trend in the employment rate from Low to Very High. However, as evidenced by the quartiles shown in each violin in Figure 2, the change across these bins is not significant.

5.2.2 NTL correlation to poverty headcount ratio at district level



Source: Authors' estimate

Figure 3: Poverty vs log of summed NTL for years 2016 (blue) and 2019 (red)

We obtained poverty statistics from surveys conducted in 2016 and 2019. Figure 3 shows the PHCR against each corresponding year's summed NTL plotted on a log scale. Here observe that most districts follow a correlation in both these years where, as the log of summed NTL increases, PHCR decreases in a somewhat linear way. We note the presence of outliers which yield some interesting information that we discuss in Section 5.2.2.1.

5.2.2.1 Economic rationale for the presence of outliers.

Why is poverty and NTL high in 2019 for Badulla?

We note that a majority of the mining and quarrying which are night time activities are registered in Badulla. This can possibly introduce production-related NTL intensities into the mix for Badulla, and that violates our assumption of consumption dominated NTL for Sri Lanka. We also note high levels of employment in the estate sector in Badulla which consists of the bulk of the employment type in the district (57.3% with a 11% land consumption in 2019). Given the fact that estate sector poverty is the highest among rural and urban sectors in Sri Lanka (Deyshappriya 2023) combined with the highest number of mining and quarrying taking place, can explain the high NTL and high poverty observed in Badulla.

Table 2: Economic activities of Badulla district

Year	Registered mining and quarrying businesses	Land consumption in agriculture (including estate sector)	Employment type in agriculture (including estate sector)	Tourism occupancy rate
2016	883 (16.9%)*	[not available]	57.3%	[not available]
2019	779 (20.3%)*	11%	55.4%	17%

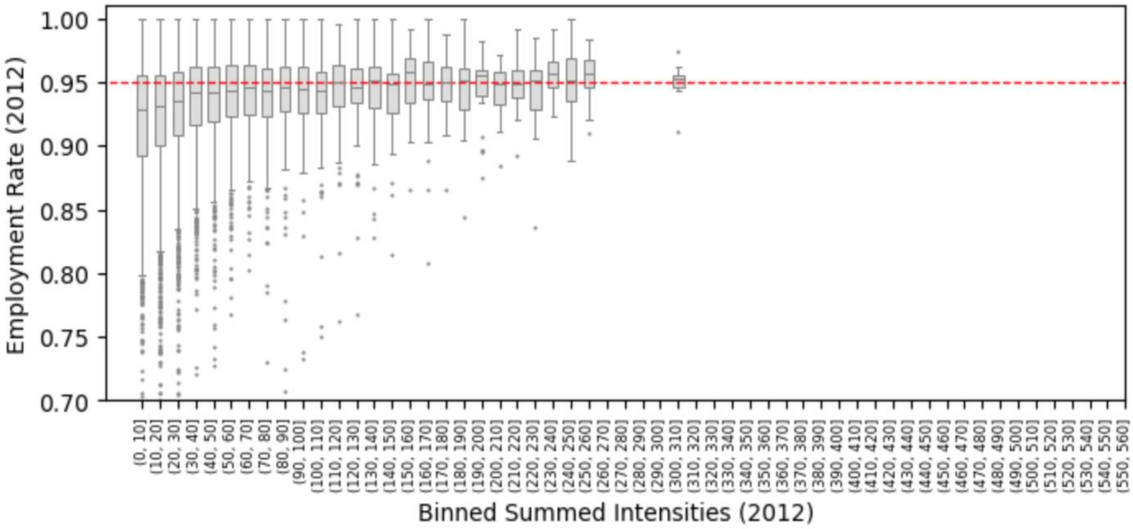
*As a percentage of the total no. of industries in the district

Source: Department of Census and Statistics

Low poverty rates in Mannar and Vavuniya given the level of NTL

Mannar and Vavuniya show very low poverty levels with low NTL, especially in 2016. This can be attributed to the post war rehabilitation and redevelopment programmes set out by the government as well as multinational organizations, which were built around cash transfers. However, despite these programmes implemented across the conflict affected areas, especially Northern province, the high poverty rates in Mullaitivu and Kilinochchi are noticeable, where this high poverty rate with low NTL has persisted even in 2019 for Mullaitivu. According to the World Bank (International Bank for Reconstruction and Development/The World Bank 2021), this could be attributed to the low infrastructure development in the area and lack of other employment opportunities outside of low productivity agriculture.

5.3 NTL correlation to economic variables at GND level



Source: Authors' estimate

Figure 4: Box plots for employment rate for NTL bins

We obtain the NTL and the employment rate for each GND. We then split NTL into bins and obtain box plots for employment rate within each NTL bin (Figure 4). When looking at these boxplots across the bins we observe that at the lower end, as NTL decreases the mean employment rate drops. However, above a certain threshold NTL value, the correlation effect seems to decrease with the employment rate showing lower elasticity with respect to NTL.

6. Discussion and Conclusions

6.1 NTL correlation to employment rate at district level

As discussed in 5.2.1, we show that the observed increase in the mean employment rate with increasing NTL is not significant, given the high RMSE and R^2 values associated with the data. Therefore we note that NTL alone might not provide enough confidence for district level employment related decision making.

6.2 NTL correlation to PHCR at district level

We observe that when considering NTL and PHCR, most districts follow a linear correlation where the log of summed NTL increases with decreasing PHCR for both 2016 and 2019. This is an interesting finding that suggests that district level poverty might be estimable using NTL data. Our outlier study showed that districts with higher employment rates in the estate sector tend to have higher poverty rates, and the districts that have mining and quarrying industries, tend to have higher NTL. When a district has a combination of both high estate sector employment as well as high mining and quarrying, they tend to present as outliers with both high NTL and high unemployment. The districts that show a low level of NTL and a low level of poverty tend to be the districts where government and foreign aid through social welfare programmes are predominantly provided which further corroborates the observed correlation.

6.3 Benefits of NTL usage

Our work shows that meaningful insights on poverty can be obtained from changes in NTL combined with other available information variables. Given the correlations we observe between PHCR and NTL at district-level for years with data availability and given the sparse availability of PHCR data in general, it might be beneficial to explore the use of NTL for augmenting poverty analyses at district level in years without PHCR data.

7. Limitations

(Henderson, Storeygard, and Weil 2012) identifies using NTL for measuring economic activity as using the consumption approach to calculating GDP to a certain extent. A concern with this method according to (Iddawela 2024), is the exposure to double counting errors. GDP can be calculated through production method, Income method and expenditure method. And there is a possibility of capturing the night time production activities through the NTL approach. Even though this is a valid concern with regards to countries that heavily engage in night time production activities, in Sri Lanka, they are extremely limited. Even industrial activities such as mining and quarrying that usually take place at night only add up to 2.6% of GDP in 2017. Therefore it is reasonable to assume that double counting error is either non-existent or insignificant in the case of Sri Lanka.

We also note that there could be non-linearity between NTL increase and the corresponding increase in economic activity. Simply put, one unit increase in GDP does not translate to a proportional increase in NTL because of the limitations in sensor sensitivity and top coding which rates the luminosity from 0-63. For example, in cases where luminosity is at 63 any growth in luminosity above 63, is not recorded in the data (and still shows as 63). On the other hand, as a result of the low resolution in the data sets, the areas that show no economic activity could still have economic activity that is not captured by the satellites just because they do not emit enough light. We assume that the areas within the band of luminosity 0-63 are predominant and representative of what we try to measure.

Ratchet effect (Iddawela 2024), could occur when lights remain switched on once installed. As a result, the lights that remain switched on even during economic downturns, may cause the NTL to be a less reliable proxy for economic activity. However, according to (Henderson, Storeygard, and Weil 2012), the changes in luminosity equally predict the change in economic activity.

Another limitation of using NTL in detecting economic activity is the inability of the existing technology to capture the shorter wavelengths of LED lighting (Iddawela 2024). As a result, luminosity from areas that predominantly use LED may not be captured and recorded appropriately. However, in Sri Lanka, the use of LED lighting is still at a very minimal stage, according to (Alam et al. 2021). Thus we assume any deviations in NTL due to LEDs to be negligible.

8. Future Work

This study is based on monetary poverty data. In the future, we hope to expand this study by using multidimensional poverty data, which provides a broader picture of poverty. Further, we plan to use population normalized NTL to analyze effects on the connection between NTL and considered economic variables, independent of population changes. Moreover the data from Census of Population and Housing survey 2024, which is currently in the process of being collected, can be used to draw more timely and accurate inferences. We also note that other satellite related remote sensing data can be used to supplement the existing data and we leave this for future work as well.

References

Abeyratne, Sirimal. 2024. “CEPA Perspectives on Sri Lanka’s Crisis-Led Poverty- by Sirimal Abeyratne.” Cepa (blog). June 3, 2024. https://www.cepa.lk/blog/cepa-perspectives-on-sri-lankas-crisis-led-poverty/ .

Baud, Isa, Monika Kuffer, Karin Pfeffer, Richard Sliuzas, and Sadasivam Karuppannan. 2010. “Understanding Heterogeneity in Metropolitan India: The Added Value of Remote Sensing Data for Analyzing Sub-Standard Residential Areas.” International Journal of Applied Earth Observation and Geoinformation 12 (5): 359–74. https://doi.org/10.1016/j.jag.2010.04.008 .

Chen, Liming, Yang Lu, and Aruna Nanayakkara. 2021. “Rural Road Connectivity and Local Economic Activity: Evidence from Sri Lanka’s Integrated Road Investment Program.” https://doi.org/10.22617/wps210484-2 .

Daniele, Ehrlich, Schiavina Marcello, Pesaresi Martino, Kemper Thomas, and Joint Research Centre (European Commission). 2018. Detecting Spatial Pattern of Inequality from Remote Sensing. Publications Office of the EU. https://doi.org/10.2760/642218 .

Deepawansa, D Dilshanie. 2023. Revealing Sri Lanka’s Multidimensional Poverty Interview by Multidimensional Poverty Peer Network. https://www.mppn.org/revealing-sri-lankas-multidimensional-poverty/#:~:text=The%20Department%20of%20Census%20and,and%20Expenditure%20Survey%20(HIES) .

Department of Census and Statistics, Unicef, and Oxford Poverty and Human Development Initiative. n.d. “Multidimensional Poverty in Sri Lanka.” The Oxford Poverty and Human Development Initiative. https://ophi.org.uk/sites/default/files/2023-12/mpi_in_sri_lanka_briefing_2021.pdf .

Deyshappriya, N. P. Ravindra. 2023. “Economic Crisis, Inflation and Poverty in Sri Lanka.” The London School of Economics and Political Science (blog). January 2, 2023. https://blogs.lse.ac.uk/southasia/2023/01/02/economic-crisis-inflation-and-poverty-in-sri-lanka/ .

Elvidge, Christopher D, Kimberly Baugh, Mikhail Zhizhin, Feng Chi Hsu, and Tilottama Ghosh. 2017. “VIIRS Night-Time Lights.” International Journal of Remote Sensing 38 (21): 5860–79. https://doi.org/10.1080/01431161.2017.1342050 .

Eun, Jaemin, and Sergii Skakun. 2022. “Characterizing Land Use with Night-Time Imagery: The War in Eastern Ukraine (2012-2016).” Environmental Research Letters, August. https://doi.org/10.1088/1748-9326/ac8b23 .

GIS Branch, Survey Department of Sri Lanka. n.d. “Grama Niladari Boundary Map of Sri Lanka.” Survey Department of Sri Lanka. https://services.survey.gov.lk/gn_updating/ .

Google Earth Engine. n.d.a “VIIRS Nighttime Day/Night Band Composites Version 1 | Earth Engine Data Catalog | Google for Developers.” Google for Developers. https://developers.google.com/earth-engine/datasets/catalog/NOAA_VIIRS_DNB_MONTHLY_V1_VCMCFG .

———. n.d.b “VIIRS Stray Light Corrected Nighttime Day/Night Band Composites Version 1 | Earth Engine Data Catalog.” Google for Developers.

https://developers.google.com/earth-engine/datasets/catalog/NOAA_VIIRS_DNB_MONTHLY_V1_VCMSLCFG .

Henderson, J. Vernon, Adam Storeygard, and David N Weil. 2012. "Measuring Economic Growth from Outer Space." American Economic Review 102 (2): 994–1028. https://doi.org/10.1257/aer.102.2.994 .

Iddawela, Yohan. 2024. "Some Surprising Facts about Nightlights Data." Spatial Edge (blog). February 28, 2024. https://www.spatialedge.co/p/some-surprising-facts-about-nightlights .

Jayaratne, W., S.W.S.B. Dasanayaka, Omar Al Serhan, Isra A Alam, and Fatin Samara. 2021. "Market Perception of Efficient Light Source Technologies: A Case Study on Sustainable Energy Transitions in Sri Lanka." International Journal of Business Performance Management 23 (1/2): 4–4. https://doi.org/10.1504/ijbpm.2022.119548 .

Kim, Dawool. 2022. "Assessing Regional Economy in North Korea Using Nighttime Light." Asia and the Global Economy 2 (3): 100046. https://doi.org/10.1016/j.aglobe.2022.100046 .

Li, Minying, Jinyao Lin, Zhengnan Ji, Kexin Chen, and Jingxi Liu. 2023. "Grid-Scale Poverty Assessment by Integrating High-Resolution Nighttime Light and Spatial Big Data—a Case Study in the Pearl River Delta." Remote Sensing 15 (18): 4618–18. https://doi.org/10.3390/rs15184618 .

Li, Xi, Rui Zhang, Chengquan Huang, and Deren Li. 2015. "Detecting 2014 Northern Iraq Insurgency Using Night-Time Light Imagery." International Journal of Remote Sensing 36 (13): 3446–58. https://doi.org/10.1080/01431161.2015.1059968 .

Nanayakkara, Wimal. 2017. "Talking economics - Status of Poverty in Sri Lanka Based on Different Poverty Lines." IPS. March 30, 2017. https://www.ips.lk/talkingeconomics/2017/03/30/status-of-poverty-in-sri-lanka-based-on-different-poverty-lines/ .

Newhouse, David. 2017. Part II: Understanding Poverty in Sri Lanka Interview by World Bank Group. https://www.worldbank.org/en/news/feature/2017/03/02/partii-understanding-poverty-in-sri-lanka .

Payne Institute for Public Policy. n.d. "VIIRS Nighttime Light." Eogdata.mines.edu. https://eogdata.mines.edu/products/vnl/#monthly .

Puttanapong, Nattapong, Arturo Martinez, Joseph Albert Nino Bulan, Mildred Addawe, Ron Lester Durante, and Marymell Martillan. 2022. "Predicting Poverty Using Geospatial Data in Thailand." ISPRS International Journal of Geo-Information 11 (5): 293. https://doi.org/10.3390/ijgi11050293 .

Rammohan, Anu, and Achmad Tohari. 2023. "Rural Poverty and Labour Force Participation: Evidence from Indonesia's Village Fund Program." PLoS ONE 18 (6): e0283041–41. https://doi.org/10.1371/journal.pone.0283041 .

Ranawana, Anupama. 2018. "How Do We Live? Understanding Poverty in Post-War Sri Lanka." The London School of Economics and Political Science (blog). July 2, 2018. https://blogs.lse.ac.uk/southasia/2018/07/02/how-do-we-live-understanding-poverty-in-post-war-sri-lanka/ .

Sakalasooriya, Nishan. 2021. "Regional Development Disparities in Sri Lanka." Open Journal of Social Sciences 9 (7): 62–91. https://doi.org/10.4236/jss.2021.97006 .

Sebastian, Ashwini, Shivapragasam Shivakumaran, Ani R Silwal, David Newhouse, Thomas Walker, Nobuo Yoshida, and Poverty and Equity Global Practice Group. 2018. "A Proxy Means Test for Sri Lanka." World Bank. https://documents1.worldbank.org/curated/zh/589691540834569022/pdf/131470-NWP-173-A-Proxy-Means-Test.pdf .

Shanmugarajah, Yashothara, and Merl Chandana. 2020. "The State of the Art in Leveraging Public Domain Remote Sensing Data for Development Purposes." Lirneasia. https://lirneasia.net/wp-content/uploads/2020/05/The-State-of-the-Art-In-Leveraging-Public-Domain-Remote-Sensing-Data-for-Development-Purposes.pdf .

Stevens, Ann Huff, and Ariel Marek Pihl. 2016. "Labor Markets and Poverty in the US: Basic Facts, Policy and Research Needs." UC Davis (blog). https://poverty.ucdavis.edu/research-paper/labor-markets-and-poverty-us-basic-facts-policy-and-research-needs .

Subash, S P, Rajeev Ranjan Kumar, and K S Aditya. 2018. "Satellite Data and Machine Learning Tools for Predicting Poverty in Rural India." Agricultural Economics Research Review 31 (2): 231. https://doi.org/10.5958/0974-0279.2018.00040.x .

The Directorate-General for Economic and Financial Affairs European Commission. 2023. "The Joint Harmonised EU Programme of Business and Consumer Surveys." European Commission. https://economy-finance.ec.europa.eu/system/files/2023-02/bcs_user_guide.pdf .

The World Bank. 2021. "Economic and Poverty Impact of COVID-19." The World Bank. The World Bank. https://thedocs.worldbank.org/en/doc/15b8de0edd4f39cc7a82b7aff8430576-0310062021/original/SriLanka-DevUpd-Apr9.pdf .

Townsend, Alexander C., and David A. Bruce. 2010. "The Use of Night-Time Lights Satellite Imagery as a Measure of Australia's Regional Electricity Consumption and Population Distribution." International Journal of Remote Sensing 31 (16): 4459–80. https://doi.org/10.1080/01431160903261005 .

World Bank Group. 2021. "Sri Lanka Poverty Update: Background Report to Sri Lanka Poverty Assessment." World Bank. International Bank for Reconstruction and Development / The World Bank. https://documents1.worldbank.org/curated/en/703091634229318506/pdf/Sri-Lanka-Poverty-Update-Background-Report-to-Sri-Lanka-Poverty-Assessment.pdf .

Xie, Bin, and Yan Liu. 2018. "Visualizing Australia's Urban Extent: A Comparison between Residential Housing Addresses and Night-Time Light Data." Regional Studies Regional Science 5 (1): 365–68. https://doi.org/10.1080/21681376.2018.1526648 .

Appendix

A. Nighttime Light Data

This study utilizes VIIRS (Visible Infrared Imaging Radiometer Suite) Nighttime Light Data, which is publicly available via Google Earth Engine. The dataset is provided by the Earth Observation Group (EOG) at the Payne Institute for Public Policy, Colorado School of Mines. EOG is a leading institution in the field of nocturnal remote sensing technology, and has been collecting satellite imagery to generate high-quality global nighttime light maps.

The Earth Observation Group (EOG) [4] has been producing Nighttime Light maps since 1994 using data from the Operational Linescan Sensor (OLS) on the DMSP. With the launch of the Joint Polar-orbiting Satellite System (JPSS), the Visible and Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) aboard JPSS satellites has significantly enhanced low-light imaging, enabling EOG to provide high-quality nighttime light data.The VIIRS DNB, operated by NASA and NOAA, offers several key improvements over OLS, including a vast reduction in the pixel footprint (Ground Instantaneous Field of View [GIFOV]), uniform GIFOV from nadir to edge of scan, lower detection limits, wider dynamic range, finer quantization, and in-flight calibration (Elvidge et al. 2017).

VIIRS Data

The Visible Infrared Imaging Radiometer Suite (VIIRS), onboard the Suomi National Polar-orbiting Partnership (SNPP) and NOAA-20 satellites, provides global data on night-time lights and surface radiance. VIIRS captures high-resolution, low-light imagery with greater sensitivity compared to earlier satellite systems, making it a powerful tool for monitoring human activities.VIIRS collects the global nighttime light imagery for every 24 hours.

VIIRS night-time lights (VNL) is derived through a series of advanced filtering and averaging processes. These steps ensure that only reliable, surface-related light data is retained. The filtering removes various contaminating factors, including sunlight, moonlight, clouds, lightning, auroras, and atmospheric glow, which could distort the night-time observations.

For this analysis, both stray light-corrected and non corrected VIIRS DNB datasets were utilized. Given that the stray light-corrected data is only available from 2014 onwards, the non-corrected dataset was used for the Grama Niladhari Level (GND) analysis for the year 2012.

[4] (Payne Institute for Public Policy, n.d.)

1. VIIRS Nighttime Day/Night Band Composites Version 1(2012-2024) [5]

The VIIRS Nighttime Day/Night Band Composites Version 1 (available via Google Earth Engine: NOAA/VIIRS/DNB/MONTHLY_V1/VCMCFG) consists of monthly average radiance composite images produced from nighttime data collected by the VIIRS DNB between April 1, 2012, and June 4, 2024.

2. VIIRS Stray Light Corrected Nighttime Day/Night Band Composites Version 1 (2014-2024)[6]

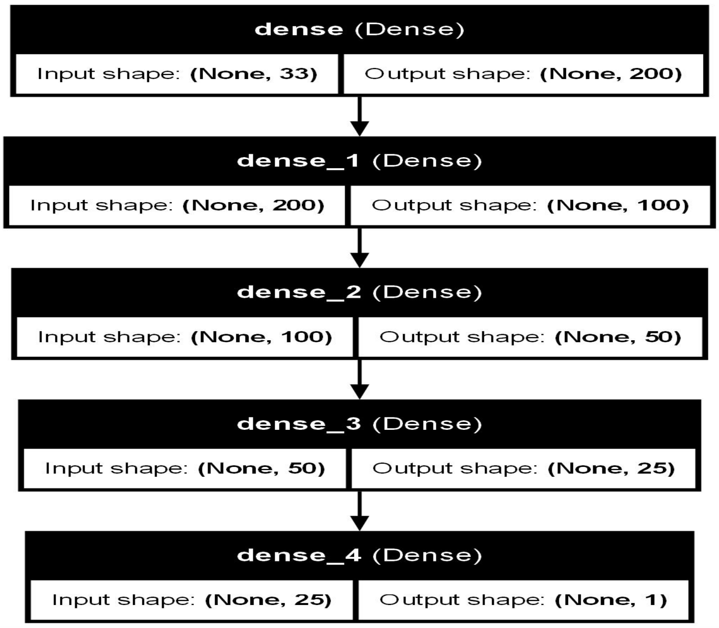
The VIIRS Stray Light Corrected Nighttime Day/Night Band Composites Version 1 (available via Google Earth Engine: NOAA/VIIRS/DNB/MONTHLY_V1/VCMSLCFG) provides monthly average radiance composite images derived from nighttime data collected by the VIIRS DNB between January 1, 2014, and June 4, 2024. This is an alternative version of the VIIRS DNB that applies a procedure to correct for stray light, extending visible coverage closer to the poles and enhancing the dynamic range.

The Stray Light Corrected VIIRS DNB data addresses issues caused by stray light contamination, extending usable coverage closer to the poles and improving the dynamic range of the radiance measurements. This makes it better suited for some regions compared to the non-corrected VIIRS DNB data, which is more prone to stray light interference. However, the correction process in the stray light version can introduce artifacts, especially in twilight regions. Both datasets exclude cloud-affected data and have not yet filtered out temporary light sources like auroras or fires.

B. ANN Architecture

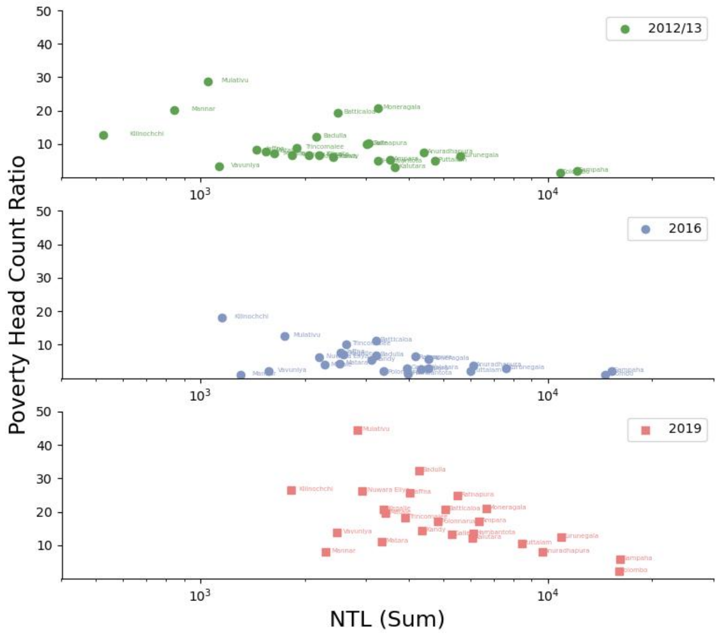
The ANN network consists of four dense layers with the input layer having 200 neurons and the subsequent hidden layers having 100, 50, and 25 neurons, respectively, each using a ReLU activation function. The final layer consists of a single neuron, which outputs the predicted value. Min-Max Scaler was used before training the ANN model to normalize the data by scaling each feature to a range between 0 and 1. The model was trained using the Adam optimizer with a learning rate of 0.001.

[5] (Google Earth Engine, n.d.a)
[6] (Google Earth Engine, n.d.b)



Source : Authors' estimate

C. Non-stray-light corrected NTL against PHCR



Source : Authors' estimate

Figure C1: Poverty vs log of summed NTL for years 2012/13 (green), 2016 (blue) and 2019 (red) using non stray light corrected data.

We obtained NTL data which was not stray light corrected for all years from 2012 onwards. In Figure C1, we present the same correlations found in Figure 3 here, but with the addition of the correlation for 2012/13. We observe that the correlation still holds. However, we note large differences in NTL intensity between stay-light corrected and non stray-light corrected plots for certain districts like Badulla.

D. More information on how poverty is calculated in Sri Lanka.

OPL is calculated using the Colombo Consumer Price Index (CCPI) following the Cost of Basic Needs Approach (CBN), which defines a consumption bundle including both food and non food items that is adequate to meet the nutritional requirements, and estimates the cost of purchasing that consumption bundle.The OPL was first introduced in Sri Lanka in 2004, and at the time, it was based on the HIES reported living standards and consumption behavior from 2002, adjusted to inflation using CCPI. But as a result of the alterations in spending and consumption habits that take place over time, the original OPL was required to be updated to capture the current context. As a result the OPL was revised in 2016, based on the 2012/13 HIES data, and adjusting to inflation with CCPI and National Consumer Price Index (NCPI).

ADVOCATA