PREDICTING GROSS DOMESTIC PRODUCT OF SRI LANKA USING NIGHTTIME LIGHT DATA

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E H G C Pathmasiri

B M Sumanaratne

Abstract

The main objectives of this study were to develop a model for accurately predicting Sri Lanka's GDP using nighttime light (NTL) imagery, address existing limitations in current models, and enhance the precision of socioeconomic data extraction. The study utilised Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) image data from 1992 to 2013 and Visible Infrared Imaging Radiometer Suite (VIIRS) image data from 2013 to 2019, along with Sri Lanka's official GDP data. The total DN (Digital Number) value for each year was then extracted and correlated with Sri Lanka's official/published GDP. The study yielded two major findings. First, while many models exist for correcting and converting DMSP and VIIRS datasets to measure socioeconomic status, some of these models fail to produce favourable results in the context of Sri Lanka. Second, the model adopted in this study measured Sri Lanka's GDP with high accuracy. The significance of the linear regression model shows that processed data based on the model developed in the current study are more suited for estimating GDP in Sri Lanka. Therefore, it can be concluded that the NTL image processing model used in this study is a valid and accurate approach for measuring GDP using NTL data.

JEL: *E01, C22, R11, O47, C55, Q40, R15*

Keywords: *DMSP-OLS NTL image, Electric power consumption, GDP, NTL Images, VIIRS images*

E H G C Pathmasiri
Department of Geography
University of Ruhuna, Sri Lanka
Email: pathmasiri@geo.ruh.ac.lk, https://orcid.org/0000-0002-2998-5304

B M Sumanaratne (Corresponding Author)
Department of Economics
University of Ruhuna, Sri Lanka
Email: bmsumana@econ.ruh.ac.lk, https://orcid.org/0009-0006-7648-5309

INTRODUCTION

Electric power consumption is a cause and a result of the economic development of a society. Hence, nighttime light (NTL) is a representation of the socioeconomic status of a society. Compared to other remote sensing satellite observations, nighttime light remote sensing imagery can reflect human activity (Li et al., 2016). Several NTL image datasets collected from various sensors and platforms are available for remote sensing purposes (Huang et al., 2014; Li et al., 2020). While every data source contains different errors and limitations, different models and techniques have been developed by researchers to extract more accurate information from NTL imagery. However, these models also have some limitations, and some models cause spatially misleading calculations, especially when used to extract data on socio-economic information in developing countries such as Sri Lanka. It is therefore important to check whether those models are accurate in terms of time-space dimensions.

Under these circumstances, the main objective of this study is to develop a model that can be used for extracting GDP more precisely using NTL data. The article first describes the characteristics of and errors arising from nighttime light images, the models suggested by various researchers to minimise them, and the models that can be used to extract information on socio-economic activities from multiple sources, such as DMSP-OLS NTL images and VIIRS Images. Second, the model developed by this study, which can be used to extract information from multiple sources, is presented step by step. Third, it illustrates the extent to which the model is suitable for extracting accurate information on Sri Lanka's GDP through nighttime light imagery. Only a very few researchers (such as Pathmasiri and Kim, 2018; Zhou et al., 2015) have used NTL image data for measuring the socio-economic status in Sri Lanka. In addition to that, although there are many models developed to correct the NTL image data and measure the socio-economic information based on NTL images, some of them are unable to measure Sri Lanka's socio-economic states precisely. Thus, the main objective of the study is to develop a model that can be used to accurately predict the GDP of Sri Lanka using NTL image data.

MATERIALS AND METHODS

Several NTL image datasets that were collected from various sensors and platforms are available for remote sensing purposes. Some of them are DMSP-OLS (Defense Meteorological Satellite Program / Operational Linescan System), Suomi NPP-VIIRS (Suomi National Polar-orbiting Partnership / Visible Infrared Imaging Radiometer Suite), ISS (International Space Station), EROS-B (Earth Resources Observation Satellite-B), JL1-3B (Jilin-1 Satellite 3B), JL1-07/08 (Jilin-1 Satellites 07 and 08), LJ1-01 (Luojia-1 Satellite 01). However, two of them, namely the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) image data and the Visible Infrared Imaging Radiometer Suite (VIIRS) image data, are widely used by researchers due to their free accessibility. DMSP-OLS data are published by the National Oceanic and Atmospheric Administration's National Geophysical Data Center (NOAA-NGDC). NOAA-NGDC provides temporally calibrated DMSP-OLS NTL time series data from 1992–2013. The study utilized the stable lights dataset from the DMSP-OLS nighttime light imagery, which comprises three types of datasets: cloud-free coverage, average visible, and stable lights. Due to the unavailability of DMSP-OLS data for years after 2013, researchers have used the image data produced by the Visible Infrared Imaging Radiometer Suite (VIIRS) instrument onboard the Suomi National Polar Partnership (NPP) satellite launched in October 2011. Both image datasets have distinct characteristics as depicted in Table 1. DMSP-OLS NTL and VIIRS images were processed, as described later, to compute the total number of lit pixels (TNLP) and the sum of digital number values (SDNV) for each year from 1992 to 2019. Linear and nonlinear relationships between TNLP, SDNV, and GDP were then analyzed using published nominal GDP data for Sri Lanka from CountryEconomy.com (2024). The most suitable relationships were selected based on the coefficient of determination (R^2) values.

Table 1: Characteristics of the freely accessible DMSP-OLS and VIIRS datasets

Characteristics	**DMSP-OLS dataset**	**VIIRS dataset**
Satellite	Six of DMSP satellites (F10, F12, F14, F15, F16 and F18).	Suomi NPP
Inter-calibrated data or not	Not inter-calibrated data	Inter-calibrated data
Spatial resolution	30 arcsecond	15 arcsecond
Time span	1992-2013	2012-2020
Temporal resolution	1 per year	1 per month
Spectral Bands	Panchromatic 400-1100 nm	Panchromatic 505-890 nm
Radiometric resolution	6 bits	14 bits
Available dataset types	Cloud-free Coverage	Cloud-free Coverage
	Average Visible	Could Coverage
	Stable Light	

Sources: created based on Huang et al., 2014; Li et al., 2020

NTL Data Correcting Models in the Literature

The above-mentioned inheritance characteristics of DMSP-OLS NTL data produce several weaknesses (Pathmasiri and Kim, 2018), such as

- Huge discrepancies between the Sum of Digital Number Values (SDNV) of images derived from different satellites for the same year,
- Abnormal fluctuations in DN values (for the same geographic location) for different years derived from the same satellite,
- Huge discrepancies in the Total Number of Lit Pixels (TNLP) between two satellites for the same year,
- Abnormal fluctuations in the number of lit pixels of images derived from the same satellite for different years.

Researchers have developed several techniques to overcome some of the shortcomings. Due to the absence of an onboard calibration system, original DMSP-OLS-NTL images are not inter-calibrated. Therefore, to inter-calibrate the images, researchers use the Invariant Region Method. Based on the invariant region method, Elvidge et al. (2009) and Liu et al. (2012) proposed second-order polynomial regression models to inter-calibrate the DMSP-OLS NTL images. In contrast, Hsu et al. (2015) introduced a linear regression model. Hara et al. (2004) and Letu et al. (2012, 2016) introduced two models for saturation effect correcting the linear correlation model and the cubic regression equation model, respectively. The intra-annual stable lit pixel identification and averaging method (Liu et al., 2012) and the intra-annual lit pixel averaging method (Zhao et al, 2015) are the most commonly used methods to remove unstable lit pixels. Several models also have been developed for inter-annual series correction, i.e., to reduce inter-annual discrepancies of SDNV and TNLP. As per the model developed by Liu et al. (2012), the DN value of each pixel in an early annual image will not be larger than in a later annual image. As per Cao et al.'s (2016) model, a lit pixels detected in an annual NTL image in an earlier year should not disappear in a later year and a lit pixel's DN value should not be less than the DN value of the lit pixel in the same geographic location the following year. Therefore, if the DN value of a lit pixel does not increase, the DN value of the pixel remains the same for future annual images.

As depicted in Table 1 (above), VIIRS data have specific characteristics. In contrast to the DMSP-OLS data, on the one hand, VIIRS data have a fine spatial resolution, radiometric resolution, and temporal resolution. On the other hand, the temporal span of VIIRS data is only from 2012 to the present. Also, different from the DN values in the DMSP data, the records in the VIIRS are the radiance of NTL data. Thus, both datasets cannot be used together without harmonising. Li et al. (2017, 2020), Zhao et al. (2019), and Zheng et al. (2019) have developed mathematical models for converting the VIIRS radian data to DMSP-like data.

The harmonisation approach most commonly used by researchers consists of seven steps:

- Step 1: Generating annual VIIRS composition data from the monthly observations: For compositing annual VIIRS data, Li et al. (2020) have used the weighted average approach by considering the number of cloud-free observations and the annually composited radiance values from monthly data. Zhao et al. (2017 & 2019) have used the simple average approach, i.e., by averaging the pixel brightness of all data in each year.
- Step 2: Transforming spatial resolution of VIIRS data to 30 arc-seconds: Li et al. (2017, 2020) and Zhao et al. (2019) have used the Kernel Density approach with a symmetric Gaussian point-spread function and a moving circle window of 5 times the VIIRS pixel size.
- Step 3: Implementing a logarithmic transformation on derived Kernel Density maps for further adjusting the VIIRS data to DMSP data.

- Step 4: Adding a constant value (number one) to avoid the generation of invalid values during the logarithmic transformation.
- Step 5: Quantifying the relationship between processed VIIRS and DMSP NTL data in 2013 using a sigmoid function.
- Step 6: Converting VIIRS data into DMSP-OLS-like data, using the result of the 5th step. Li et al. (2020) and Zhao et al. (2019) have identified sigmoid relationships between DMSP and the processed VIIRS imageries on the global scale and the South East Asia scale in 2013 and have derived Determined-Parameter Values (DPV) for sigmoid models (Equation 1) accordingly. The determined parameters of 'a', 'b', 'c', and 'd' of the Li et al (2020) model were 6.5, 57.4, 1.9, and 10.8, respectively.

$$f(x) = a + b\left(\frac{1}{1+e^{-c(x-d)}}\right) \text{ --- } (1)$$

- Step 7: Setting minimum DN value: Li et al. (2020) have used the value 6.5 (the value 'a' of the DPVs) as the minimum DMSP-like value.

Although there are many mathematical models available in the literature for refining the data, the application of some models would produce more imprecise results than others. Pathmasiri and Kim (2018) illustrate the potential of different models in generating data on the socio-economic status of Sri Lanka using DMSP-OLS NTL images.

As discussed in the VIIRS data correction process of this study, some of the previously developed models cannot be applied to refine VIIRS data for extracting meaningful information on the socio-economic context of Sri Lanka. Firstly, as Sri Lanka is located in the tropics, VIIRS NTL images related to Sri Lanka are more affected by clouds than in non-tropical parts of the world. Therefore, it seems that the application of the Simple Averaging model developed by Zhao et al. (2017 and 2019) to generate annual VIIRS composition data is unsuitable. Secondly, the application of global-scale DPV for country-level analysis leads to an underestimation of the socio-economic characteristics of developing countries (Pathmasiri & Kim, 2018). Thirdly, Li et al. (2020) have defined the minimum DN value arbitrarily. In such circumstances, the main objective of the study is to develop a model that can be used to accurately measure the socio-economic status, specifically GDP, of Sri Lanka using NTL data.

NTL Data-Correcting Model Adopted in the Present Study

As mentioned above, two types of images, i.e., DMSP-OLS NTL images and VIIRS images, are used in the study. Because of their inherent characteristics, the datasets must be corrected separately.

Therefore, the data correction process in the study consists of two parts: DMSP data correction and VIIRS data correction.

DMSP-OLS NTL Data Correcting Model

To overcome the shortcomings of DMSP-OLS NTL data, the following seven-step model was adopted.

- Step 1: For easy data handling, the image portion covering the territory (land) of Sri Lanka was extracted from each original DMSP-OLS NTL image.
- Step 2: *Inter-calibration* was performed for the extracted DMSP-OLS NTL stable light images by using the same parameters that were developed by Huang et al. (2019).
- Step 3: As per to Zhao et al. (2015), there are many unlit pixels in original NTL images that have non-zero DN values created by background noise and that are added by the non-zero constants in quadratic polynomial regression equation-based calculations. To remove those non-zero DN values from images, each image was processed based on Equation 2. Thereby, the pixels in the original images having a DN value less than 3 were converted to a DN value of 0.

  $DN_{n,i} = 0, if\left(DN_{n,i} \leq 3\right);\ \ DN_{n,i} = DN_{n,i}, if(otherwise)$ ------------------ (2)

  where ‘n’ represents each annual image and ‘i’ represents each pixel of the image.
- Step 4: For some years, two images were captured by two sensors. However, it was identified that abnormal fluctuations exist in the total number of lit pixels and in the sum of DN values of those intra-annual images. As identified by Pathmasiri and Kim (2018), the intra-annual correction method adopted by Liu et al. (2012) is more precise for resolving this issue. Thus, in the study, the intra-annual corrections (IAC) were performed by identifying intra-annual stable lit pixels and averaging their DN values. In this process, each lit pixel in both images for the same year was identified as a stable lit pixel, and the resulting annual image consisted of only those stable lit pixels.
- Step 5: Use of Liu et al. (2012) and Cao et al. (2016) adopted DMSP-OLS NTL inter-annual series correction methods in the Sri Lanka context is inappropriate (Pathmasiri and Kim, 2018) because both methods guarantee the continuous growth of the SDNV and TNLP. Thus, following Pathmasiri and Kim (2018), the DN values of the pixels of the resulting inter-annual images were corrected based on three annual images using Equation 3 to guarantee the following three criteria.
  - If the DN value of a pixel of the (n-1)th image and (n+1)th image is zero (0), the DN value of the pixel of the (n)th image also should be zero.
  - If the DN value of the (n)th image is zero and the DN values of (n-1)th image and (n+1)th image are more than zero, the DN value of the (n)th

image should be the average of the DN values of (n-1)th and (n+1)th images.
  - Otherwise, the DN value of the (n)th image should not be changed.

$$DN_{n,i} = 0, if\ (DN_{n-1,i} = 0)\ \&\ (DN_{n+1,i} = 0);$$
$$DN_{n,i} = \left(\frac{DN_{n-1,i}+DN_{n+1,i}}{2}\right), if\ (DN_{n-1,i} > 0)\ \&\ (DN_{n+1,i} > 0)\ \&\ (Dn_{n,i} = 0);$$
$$DN_{n,i} = DN_{n,i}, if(otherwise) \text{ -- (3)}$$

The selected annual image, the earlier annual image (n-1), and the later annual image (n+1) are represented by 'n', 'n-1', and 'n+1' respectively, while 'i' represents each pixel of the image.

- Step 6: At the 3rd step, we removed the non-lit pixels that had DN values less than 5. However, through the above calculation process, the DN values were changed. Thus, to readjust the minimum DN value limit, all the lit pixels that have a DN value less than 5.5 were converted to non-lit pixels by adopting Equation 4.

$$DN_{n,i} = 0, if(DN_{n,i} \leq 5.5);\ \ DN_{n,i} = DN_{n,i}, if(otherwise) \text{ ---------------- (4)}$$

where 'n' represents each annual image and 'i' represents each pixel of the image.

- Step 7: Finally, the lit pixel information from the processed images that cover the Sri Lankan land area was extracted.

VIIRS Data Correction

DMSP and VIIRS datasets cannot be used together for time series analysis without harmonising due to their unique characteristics (Li et al., 2020; Zhao et al., 2019). Hence, the following six-step procedure was performed in the study.

- Step 1: Generation of annual VIIRS composition: Li et al. (2020) have used the *'weighted average approach'* by considering the number of cloud-free observations and the annually composited radiance values from monthly images, while Zhao et al. (2019) have used the simple average approach, i.e., by averaging the pixel brightness of all data in each year. In this study, the sum of pixel brightness values of all data in each year was divided by the total number of cloud-free months (i.e., out of 12) in the relevant year.

$$VIIRS_a = \frac{\sum_{m=1}^{12} VIIRS_m}{\sum_{m=1}^{12} VIIRS_{cf.m}} \text{ -- (4)}$$

- Step 2: Transformation of the spatial resolution of VIIRS data to 30 arc-seconds: The Kernel Density Approach is widely used for spatially aggregating the annual VIIRS radiance data (15 arc-seconds) to the same resolution as DMSP NTL data (Li et al., 2020; Zhao et al., 2019). The $VIIRS_a$ images were transformed to the spatial resolution of the DMSP-OLS images by converting the $VIIRS_a$ images to points and then interpolating new images using the Kriging tool of ArcGIS. The Kriging method, Semivariogram model, Search Radius, and Search Radius settings were set as Ordinary, Gaussian, Variable, and 5 points, respectively.

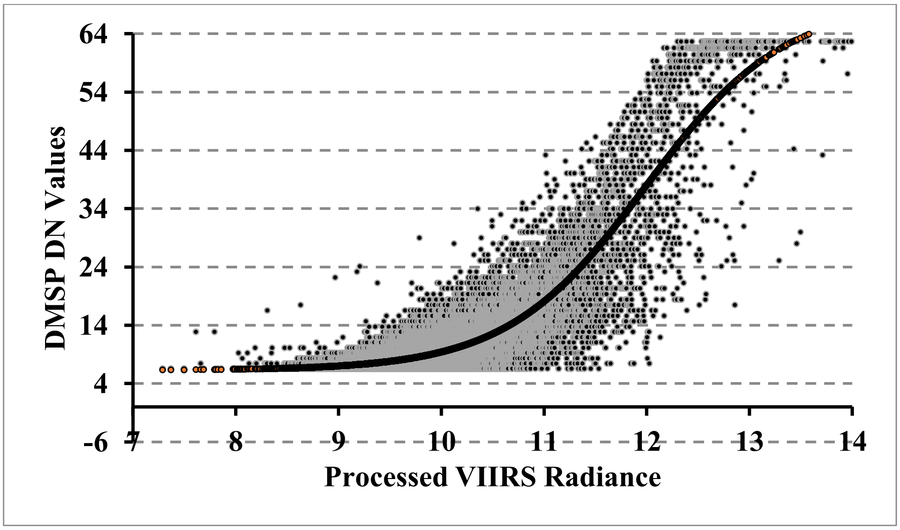
- Step 3: Logarithmic transformation: To suppress the sharp radiance and the jump within urban core areas, and to strengthen the radiance variation within suburban and rural areas (Li et al., 2020; Zhao et al., 2019), a logarithmic transformation was done on derived point density images using Equation 5. The constant value '1' was added to avoid the invalid values generated during the logarithmic transformation.

$Log\_V_{pd} = Ln(V_i + 1)$ -- (5)

where Log_V_{pd} is the logarithmic transformation of the aggregated point density result of VIIRS data V_i.

- Step 4: Quantification of the relationship between the VIIRS logarithmic data and the DMSP NTL data: There is a sigmoid relationship between the DN values of DMSP images and VIIRS logarithmic images (refer to Figure 1).

Figure 1: The sigmoid relationship between DMSP data and VIIRS logarithmic data in Sri Lanka in 2013



Source: Authors' calculations. DN values for the 2013 DMSP-OLS NTL image were computed at the end of the DMSP processing steps described above, while DN values for the 2013 VIIRS image were computed at the end of Step 3 of the VIIRS processing steps.

However, the Determining Parameter Values (DPV) of the sigmoid models vary across different areas and at different scales (Li et al., 2020; Zhao et al., 2019). The DPV for the sigmoid relationship for Sri Lanka is as depicted in Equation 6.

$$f(x) = 6.32 + 63.11\left(\frac{1}{1+e^{-1.48(x-11.99)}}\right) \text{ -- } (6)$$

where $f(x)$ is the DMSP-like DN value using the logarithmic function from the aggregated point density value of *VIIRS* x (i.e., $Log\ \_V_{pd}$).

- Step 5: Converting VIIRS logarithmic data to DMSP-like data:

  The VIIRS logarithmic data can be transformed into DMSP-like data using the sigmoid relationship. Li et al. (2020) and Zhao et al. (2019) have calculated the global scale and regional scale sigmoid relationships and have derived the Determining Parameter Values (DPV). Because the DPVs have been developed for the global scale and continental scale analysis, applying the DPVs for transforming VIIRS data of Sri Lanka will produce inaccurate data (i.e., DN values). Hence, the transformation was done using Equation 6.

- Step 6: Determining the minimum DN value (MDNV) limit:

  After transforming the VIIRS data to DMSP-like data, Li et al. (2020) and Zhao et al. (2019) have used fixed values (i.e., 6.5 and 7) as the MDNV for the DMSP-like images. However, the application of such a fixed value would produce inaccurate data.[1] Hence, the MDNV limits for the images were defined based on 'ground truth' (training signatures). The access to electricity rate of the country is almost 100%, and about 23% of the land of the country is conserved as Wildlife Areas, Natural Heritage Wilderness Areas, and Reserved Forests, within which land development activities are strictly restricted; thus, the forest area was used as the non-variant area (NVA). To do that, first, the minimum DN value of the processed VIIRS 2013 image was adjusted to guarantee that the TNLP of the image is relatively similar to the TNLP of the processed DMSP 2013 image. Then, the TNLP in the NVA mask area was calculated, and the value was used as a constant value. According to that calculation, 96% of the pixels in the NVA mask area were identified as non-lit pixels. Thus, the minimum DN values for each VIIRS image were defined to ensure that about 95% of pixels in the NVA mask area are classified as unlit pixels (or forest area). It is important to note that the value varies from year to year, as indicated in Table 2.

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[1] When these DN limits were tested in the Sri Lankan context, a large number of lit pixels were detected within protected forest areas—zones where development activities are strictly controlled and artificial lighting is minimal. This misclassification indicates that using an arbitrary fixed MDNV fails to account for regional and temporal variations in background radiance, resulting in both overestimation and underestimation of lit pixels, and consequently, a misrepresentation of actual nighttime illumination patterns.

Table 2: Ground truth-based minimum values for VIIRS data

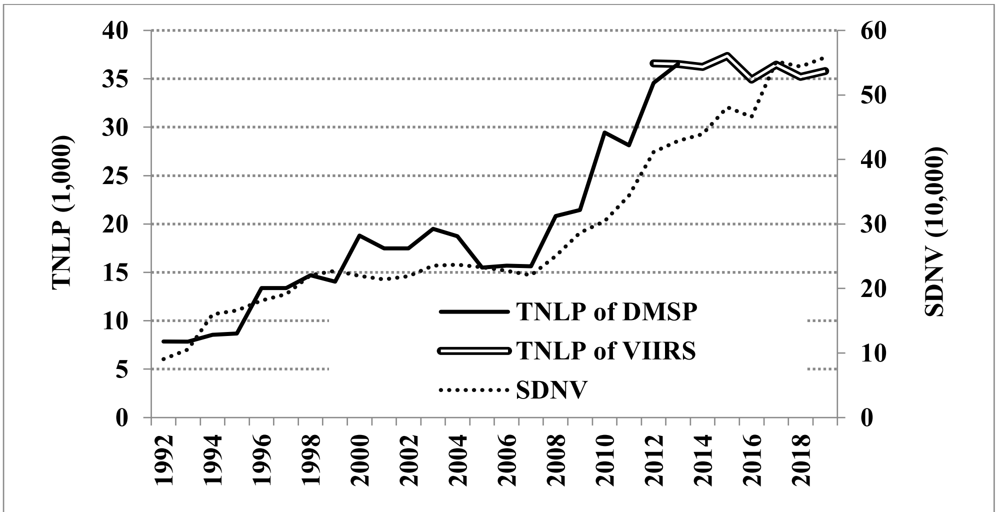
Year	Minimum DN Value	Confidence Level (%)
2012	6.01157	95.52
2013	6.08217	96.64
2014	5.81738	95.50
2015	6.32513	95.11
2016	6.04897	95.44
2017	7.08027	95.00
2018	7.30714	95.43
2019	6.88989	95.14

Source: Authors' calculations. After completing the 6th step of the VIIRS image processing, the resulting minimum DN value for each annual image was identified as the ground truth–based minimum value for the respective VIIRS data.

RESULTS AND DISCUSSION

After performing the correction, it was found that the growth pattern of TNLP in the non-forest area for each image has become stable, while the SDNV has continuously increased (refer to Figure 2).

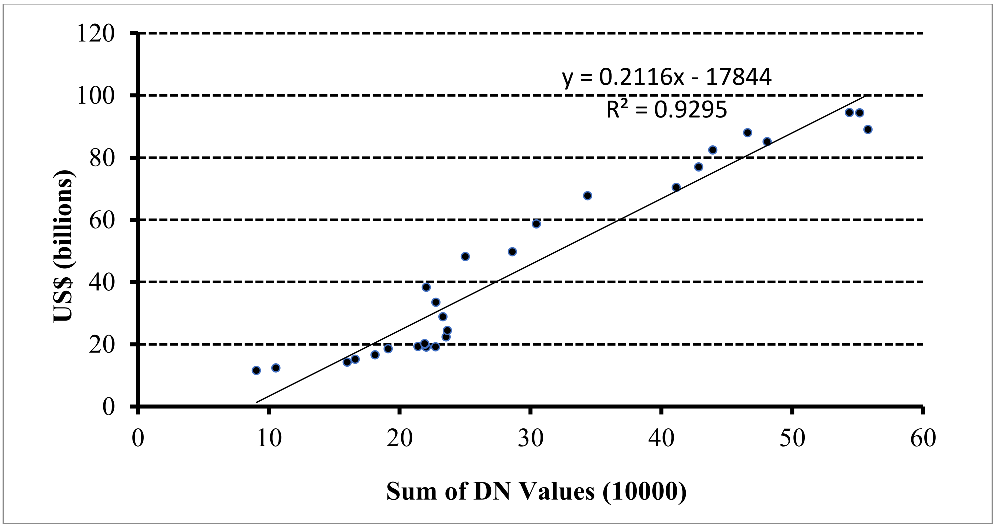
Figure 2: Growth pattern of SDNV and TNLP of images after performing the entire conversion process



Source: Authors' calculations. TNLP and SDNV were computed using DMSP-OLS NTL images for 1992–2013 and VIIRS images for 2013–2019, after completing the respective image processing steps.

Then, the paper attempts to develop a model that can be applied to accurately predict the GDP of Sri Lanka using NTL image data. In the study, both linear and nonlinear models were evaluated to identify the most suitable approach for the analysis. The selection was based on the coefficient of determination (R^2) values. Among the tested models, the linear regression model produced the highest R^2 value, indicating better performance in explaining the variance in the data. Therefore, the linear model was selected as the most appropriate for this context. As this analysis used annual nighttime light data from 1992 to 2019, the sample size of the regression model consisted of 28 observations, corresponding to the respective SDNV (and TNLP) values for each year.

Figure 3: Linear regression relationship between the Sum of DN values and the published GDP for Sri Lanka



Source: Authors' calculations

As indicated in Figure 3 (above), there is a high correlation between the published/official GDP and the SDNV of NTL images for Sri Lanka. The validity of the model and results can be checked from the results of the coefficient of determination.

Table 3: Estimated results for GDP in Sri Lanka

Variables	Estimate	Std. error	t-statistic	P-value
C	-17844.05	3684.655	-4.843	0.0001
SDN	0.212	0.011	18.522	0.0000

Sample Size: 28 observations	

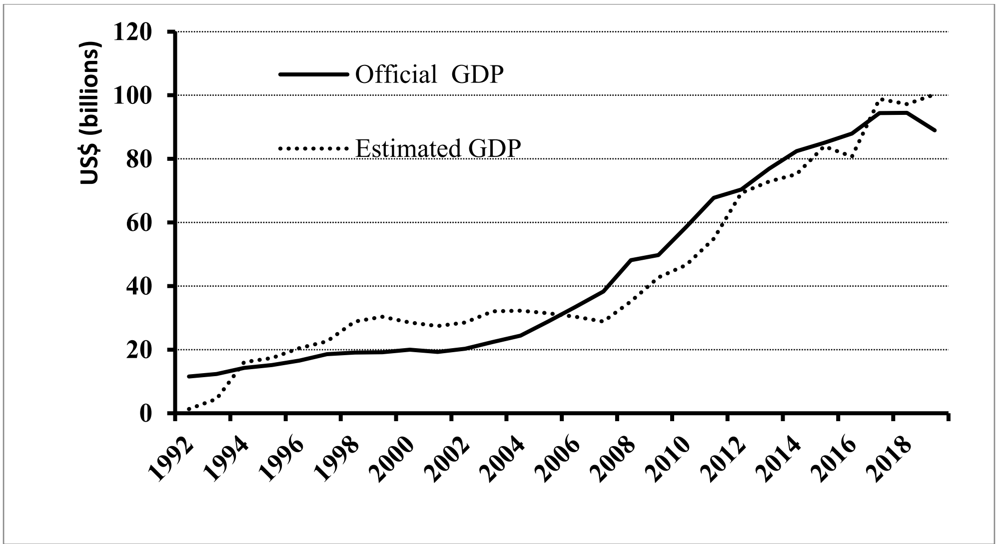
R-squared:	0.9295	Adj. R-squared:	0.927
F - statistic	343.054	Residual sum of squares:	1.71E+09

Source: Authors' calculations

From Table 3 (above), it is apparent that the estimated model is highly significant with $R^2 = 0.929$. The standard error between the published GDP and the estimated GDP that was computed based on the linear regression model is about US$ 7.8 billion. The validity of the model is evident in these figures. Hence, the linear regression model was used to calibrate the SDNV of the processed NTL images and estimate the GDP.

We can also see from Figure 4 very similar patterns in both official GDP and estimated GDP based on NTL image data, indicating that the models we used are capable of more accurately predicting the GDP of the country.

Figure 4: Relationship between official/ published GDP and the estimated GDP based on the linear regression model for Sri Lanka



Source: Authors' calculations

The discrepancy between estimated GDP values and predicted GDP values based on NTL image data could be attributed to several reasons. It is a widely held view that for effective GDP estimation using NTL at the national level, economists and researchers must first understand the factors that influence the lights-GDP relationship (Phan, 2023).

It is believed that NTL does not directly capture non-light-emitting activities such as agriculture or informal economies, which may result in underestimation or overestimation in certain areas. While this approach may be valid in industries and services where activities can be concentrated or clustered in specific locations, it is less so in agriculture and forestry (Henderson et al. 2012; Keola et al. 2014).

Additionally, this inconsistency may be due to the business environment and level of development (Dai et al. 2017). Other factors, including economic structure and urbanisation, have a significant impact on the relationship between lights and GDP. Areas with better infrastructure or more urbanisation have higher levels of nighttime lighting, which may inflate the predicted GDP value when compared to less urbanised or underdeveloped areas with comparable economic output. NTL data may not precisely epitomise service-oriented economies as it does manufacturing-based economies. For example, the financial services or IT sectors may generate high GDP with slight lighting, whereas manufacturing plants may produce more light.

Further studies, which take these variables into account, will need to be undertaken to address the issue of discrepancy in the light-GDP relationship.

CONCLUSION

In this study, the aim was to show the association between remote sensing nighttime light data and the GDP in Sri Lanka. The paper provides a model for estimating the GDP based on NTL data. Even though there are many models for harmonising and converting two NTL data products (DMSP and VIIRS) for measuring socio-economic status, some of the models cannot produce favourable results in the context of Sri Lanka. In that context, the present study created harmonised NTL data, which are longer and superior DSMP-like NTL data from 1992 to 2019. The results of the linear regression model indicate that a statistically significant relationship between NTL data and GDP can be established.

Therefore, it can be concluded that the NTL image processing model used in the study is suitable for estimating the GDP with high accuracy.

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