Evaluation of inter-calibrated nighttime light products to analyse socio-economic dynamics over Uttar Pradesh

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(Received: Nov 18, 2021; in final form: Apr 09, 2022)

Abstract: Inter-calibrated time series night time light (NTL) imagery provided by Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS) and Visible and Infrared Imaging Suite Day-Night Band (VIIRS-DNB) is widely used for various socio-economic studies. The quality of inter-calibration and integration of long-term multi-satellite data guides the extent of using NTL products as a substitute for the estimation of social and economic factors. In this study, four different DMSP-OLS and VIIRS-DNB inter-calibrated products are considered viz. (Set-A) DMSP-like using the sigmoid function (Set-B) VIIRS-like using auto-encoder model (Set-C) VIIRS-like using Random Forest, and (Set-D) VIIRS-like using Multi-Layer Perceptron are compared and accuracy is assessed of using NTL as a proxy measure for predicting the socio-economic dynamics during 2004 and 2017. The Sum of Lights (SOL) of NTL imagery is computed over Uttar Pradesh, India and statistical analysis demonstrates the correlation between the night time luminosity and all indicators ((Gross Domestic Product (GDP), energy consumption, power availability, total schools, schools electrified, birth rate and villages electrified). The VIIRS-like Set-D dataset forecasts the most accurate values of all the indicators considered ($0.53< R^2<0.90$, $p<0.001$), other than village electrification ($R^2=0.476$). It is inferred that regional-scale studies perform better using NTL datasets harmonized using the Multi-layer Perceptron technique. The DMSP-like Set-A dataset produces the next best fit for all the indicators used in this study ($0.47< R^2<0.97$, $p<0.001$). Set-B and Set-C fare poorly in the regional level comparisons. Therefore, the methodology adopted for inter-calibration highly affects the socio-economic factor estimation.

Keywords: DMSP-OLS, VIIRS-DNB, inter-calibration, socioeconomic, evaluation

1. Introduction

Remote sensing is a technique that senses and captures data remotely. It offers us an overview of urbanization, natural and human induced changes on the earth from space. Remote sensing of nighttime lights (NTL) emissions is one such way that gives us a global insight into the on-earth activities and trends. Luminosity establishes a direct relationship with the extent of urbanization in a region.

Primarily, two satellites have been used to collect and provide NTL-based products. The U.S. Air Force launched Defense Meteorological Satellite Program (DMSP) with an Operational Linescan System (OLS). It operates in visible and infrared region to collect images across a 3000 km swath, providing global coverage twice per day(Elvidge C.D., 1997). It was operational from 1992-2013 and provided 30-arc second resolution images. Post-2012, the National Aeronautics and Space Administration (NASA) and National Oceanic and Atmospheric Administration (NOAA) jointly introduced the Suomi National Polar Partnership satellite using Visible and Infrared Imaging Suite (VIIRS). It delivers improved Day Night Band (DNB) NTL products with 15-arc second spatial resolution across a 3040 km swath. It has been operational since April 2012(Cao et al., 2014). These products are freely available in the public domain by Earth Observation Group (EOG), Payne Institute for Public Policy at Colorado School of Mines.

The DMSP-OLS products have numerous shortcomings such as lack of on-board calibration and low radiometric resolution (only 6-bit), large spatial resolution (Elvidge C. et al., 2011), saturation in urban cores, and blooming effect around settlements (Sahoo et al., 2020). Also, since DMSP provides uncalibrated data, the data is reported in Digital Number rather than radiance values. Whereas, VIIRS-DNB is an upgraded sensor with onboard calibration and better spatial and radiometric resolution (14-bit). Although the blooming effect is still visible in VIIRS products, the spatial resolution of the DNB is almost 44 times smaller than the OLS imagery (Elvidge C. et al., 2011). The inconsistencies between the two data products limit the extended nighttime light-based studies (Bian et al., 2019). Inter-calibration of the two satellite data products provides extended time series to help observe and evaluate long-term regional patterns. The discrepancies between the two datasets is summarized in Table 1.

There have been studies to simulate VIIRS-like imagery from 1992 onwards or DMSP-like products since 2013. Numerous inter-calibration techniques such as regression methods (Zheng et al., 2019), statistical models (Zhang et al., 2016), power functions (Li X. et al., 2017), machine learning models like multi-layer perceptron and random forest (Sahoo et al., 2020), deep learning systems using autoencoder and convolutional neural network (CNN) models (Chen et al., 2021), etc have been developed to integrate DMSP and VIIRS NTL data. These harmonized long-term datasets have been used to analyze various factors like human well-being (Ghosh et al., 2013), Gross Domestic Product (GDP) (Sahoo et al., 2020), population density (Sutton et al., 1997), the population having access to electricity (He et al., 2014), income distribution (Ivan et al., 2020), adverse impacts of urbanization on the environment such as an increase in air and water pollution in the surrounding area (Li R. et al., 2015; Misra & Takeuchi, 2016), loss of habitat, reduced vegetation cover (Nizeyimana et al., 2001; Pandey et al., 2013), socio-

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economic development (Li D. et al., 2016; Proville et al., 2017; Prakash et al., 2019; Singhal et al., 2020; Agnihotri & Mishra, 2021), etc.

Using NTL products as a proxy measure for the estimation of these indicators depends highly on the quality of inter-calibration and integration of long-term multi-satellite data. In this study, we compare and assess the accuracy of four different DMSP-OLS and VIIRS-DNB inter-calibrated products with different socio-economic factors. Regression analysis is utilized to demonstrate the correlation between the nighttime luminosity and all indicators. This helps us realize the potential of using the Sum of Lights (SOL) as a substitute for social and economic factors and assess if SOL can be utilized for prediction. The time series for the period of 2004-2017 has been considered for the fourth largest and most populous state of India i.e., Uttar Pradesh.

2. Literature Review

Consistent analysis of various indicators over a region requires time series data. However, the discrepancies in the DMSP-OLS (1992-2013) and VIIRS-DNB (2012-present) hinder the use of NTL imagery for long-term examination. The differences highlighted in Table 1, especially the variance in the overpass time of both the satellites are a potential factor affecting the inter-calibration of DMSP and VIIRS imagery (Li X. et al., 2020). Therefore, several techniques of integration and inter-calibration of this multi-satellite NTL data have been proposed.

Earlier, regional data coverage for consistent NTL imagery was the focus of most studies. To examine the long-term impacts of the war, (Li X. et al., 2017) attempted to create an extended DMSP-like dataset for 2011-2017 using power function and Gaussian filter for the major cities in Syria. Similarly, a geographically weighted regression model was proposed in (Zheng et al., 2019) for cross-sensor calibration and generation of DMSP-like data (1996-2017) over China. In (Zhao et al., 2020), a new approach of integration has been proposed by using kernel density functions and logarithmic functions for pre-processing, following the use of sigmoid function to establish a relationship between the two satellite datasets. Thus, a harmonized (1992-2018) DMSP dataset over Southeast Asia is produced. Globally harmonized datasets have been emerging too. A similar methodology is adopted in (Li X. et al., 2020), but for global NTL coverage.

Simulation of VIIRS-like dataset has also been attempted. In (Sahoo et al., 2020), after calibration of DMSP-OLS imagery and preparation of VIIRS-DNB annual composites, two machine learning algorithms, Random Forest and Multi-Layer Perceptron, were implemented for the provision of VIIRS-like long-term data over Uttar Pradesh (2004-2017). Alternatively (Chen et al., 2021) offers a global VIIRS-like dataset for 2000-2018 introducing an Auto Encoder model and CNN to integrate the DMSP and VIIRS imagery.

These simulated temporally extended DMSP-OLS, as well as VIIRS-DNB datasets, have exhibited enormous potential in examining the regional effects of various socio-economic indicators. Research suggests a strong correlation between socioeconomic factors. Nighttime imagery has been used as a proxy indicator of GDP in (Agnihotri & Mishra, 2021), the authors used a polynomial regression model to conclude that there is a strong correlation between nighttime luminosity and GDP of India. There have been similar other studies linking the GDP of a region to the nighttime lights (Bhandari & Roychowdhury, 2011; Beyer et al., 2018; Prakash et al., 2019; Ustaoglu et al., 2021; Hu & Yao, 2021). Some studies also examined the extent of urbanization using consistent nighttime satellite imagery (Elvidge C. et al., 1997; Henderson et al., 2003; Henderson et al., 2012; Zhang & Seto, 2013; Bagan et al., 2019). Research on the relationship between multi-temporal nighttime luminosity and urbanization revealed the association of NTL with light pollution(Nizeyimana et al., 2001; Butt, 2012; Pandey et al., 2013; Han et al., 2014; Sanchez et al., 2020), mapping forest fires (Chand et al., 2007; Badarinath et al., 2011) and effects of natural catastrophes (Gillespie et al., 2007), environmental changes (Nizeyimana et al., 2001), etc. The NTL data can be used as a proxy indicator for measuring poverty (Chand et al., 2007; Gillespie et al., 2007; Prakash et al., 2019), human well-being (Ghosh et al., 2013), estimating population density, electrification rates (Elvidge C. et al., 1997, 2011; He et al., 2014), availability of power (He et al., 2014; Cole et al., 2017), education (Burchi, 2006; Henderson et al., 2012) and many other demographic and socio-economic dynamics.

3. Material and Methods

3.1. Study Area

This study has been conducted over the state of Uttar Pradesh (UP) lying in northern India. With the capital city, Lucknow UP lies between 77.1°N & 84.6°N latitudes and 23.9°E & 30.4°E longitudes. Geographically being the fourth largest state with an area of 240,928 km^2, it is the most populated part of the country with a population of 19,981,2341 (as per 2011 census (*Census Vital Data 2011, Population, Size and Decadal Change*, 2011). As of 2021, the estimated GDP of UP is about US$270 billion(*Uttar Pradesh Government*, 2021). Harbouring one of the seven worlds of wonders, it is one of the most visited tourist places in India. The state has a well-developed agricultural and industrial set-up with diverse availability of basic resources. In the recent past, UP has witnessed significant expansion of infrastructure. Therefore, the study of a state that demands almost 107,109 million units (MU) of energy per day and rising electrification rates directly affects the nighttime luminosity. Hence, it is valuable to study a region that is fast developing and a major economic contributor (Figure 1).

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Table 1. A summary of DMSP-OLS and VIIRS-DNB NTL product specifications

Satellite/Sensor	Source	Available Period	Spatial Resolution	Radiometric Resolution	Overpass time
DMSP-OLS	EOG	1992 - 2013	30-arc second	6-bit	9:30pm
VIIRS-DNB	EOG	2012 - Present	15-arc second	14-bit	1:30am

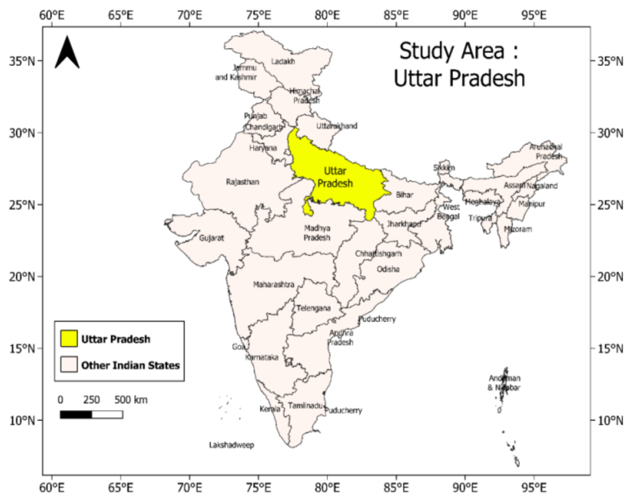

Figure 1. Location of the Study Area (UP, India)

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3.2. Night-time light satellite Data

In the present study, four consistent long-term data products have been chosen (Li X. et al., 2020; Sahoo et al., 2020; Chen et al., 2021)based upon the availability in the open domainfor the years 2004-2017. Henceforth they are referred as Set A, Set B, Set C, and Set D (Table 2). UP has been extracted from globally harmonized Set A/BB,and regionally calibrated Set C/D Figure 2 shows the composite images of 2004 for all four sets. Set A, B, C has been harmonized using the stable DMSP-OLS (version 4) and global average radiance composite images (version 1) of VIIRS-DNB imagery. Set D uses the radiance calibrated DMSP images and version 1 of VIIRS. The spatial resolution of the DMSP long-term series is 30-arc second and of VIIRS imagery is 15-arc second. The variation of SOL over the years as recorded in the four products is plotted in Figure 3

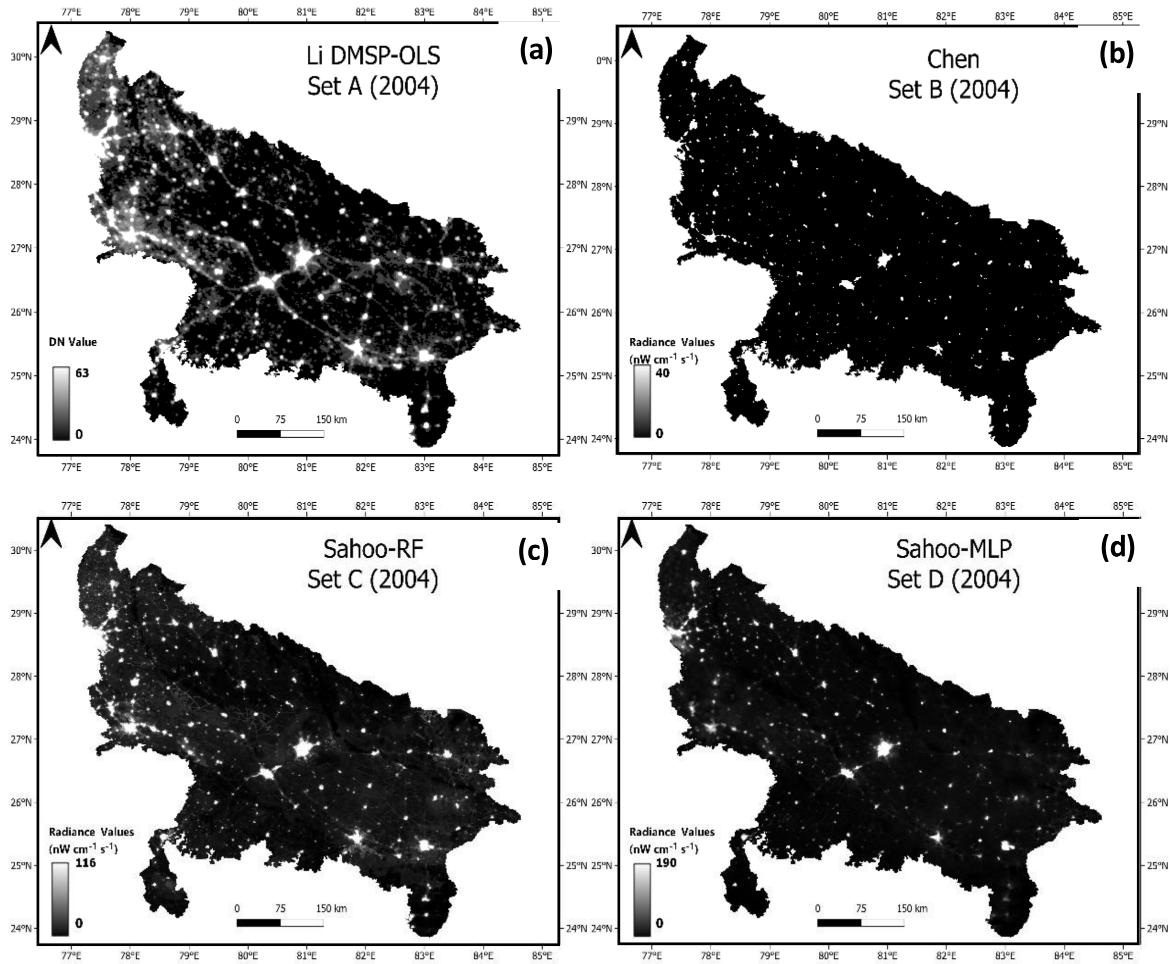

Figure 2. Inter-calibrated 2004 UP nighttime light image (a) Set A: Annual DMSP composite image (b) Set B: Annual VIIRS composite image (c) Set C: Annual VIIRS composite image (d) Set D: Annual VIIRS composite image

Table 2. Datasets chosen for the present study

Dataset	Research paper	Data	Source
A	A harmonized global nighttime light dataset 1992–2018	DMSP data (1992-2018)	Li(Li X. et al., 2020)
B	An extended time series (2000–2018) of global NPP-VIIRS-like nighttime light data from a cross-sensor calibration	VIIRS data (2000-2018)	Chen(Chen et al., 2021)
C	Inter-calibration of DMSP-OLS and SNPP-VIIRS-DNB annual nighttime light composites using machine learning	VIIRS data (2004-2017) Random Forest	Sahoo-RF(Sahoo et al., 2020)
D	Inter-calibration of DMSP-OLS and SNPP-VIIRS-DNB annual nighttime light composites using machine learning	VIIRS data (2004-2017) Multilayer Perceptron	Sahoo-MLP(Sahoo et al., 2020)

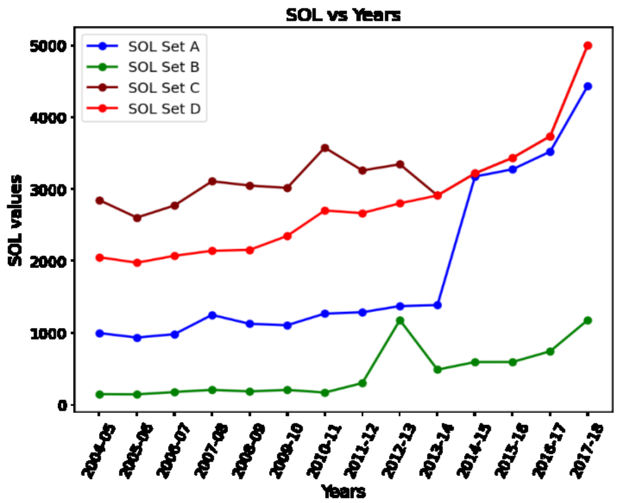

Figure 3. The growth of NTL over the years 2004-2017

Urbanization leads to gradual expansion of night time lights. The SOL values of the NTL products should be able to represent this steady incline. Figure 3 depicts the SOL values of the four products over the years. Only Set D exemplifies the trend of expansion in night time luminosity. Set A, Set B and Set C have varying SOL values due to discrepancies in inter-calibration of the raw satellite-products.

3.3. Socio-economic data

Socio-economic data is collected to indicate a country's progress and status of development in terms of human well-being. This assists in evaluating the changes required in the existing policies and to make informed decisions based on the true picture of the prevailing situation. Several markers such as education, literacy, poverty, health, employment, etc have been identified globally as a means of assessment. The available statistical records for the following factors have been extracted from 2004-2017 from the state government reports and other websites. Yearly data on many indicators is available on a privately owned Indiastat database. It provides comprehensive compiled socio-economic data for India and its states (Table 3).

Table 3. Socio-economic data used in this study

S.No.	Socio-economic Factors	Source
1	GSDP (harmonized according to 2004-5 base prices)	RBI
2	Total Energy Consumption	MOSPI
3	Per Capita Availability of Power	IndiaStat
4	Percentage of schools having electricity	UDISE
5	Total number of schools	UDISE
6	Birth rate	RBI
7	Number of villages electrified	IndiaStat

3.3.1. Gross State Domestic Product (GSDP).

GSDP is the total monetary value added by all the economic sectors within the boundaries of the state in a specified period. It is used to examine the overall well-being and standard of living in a state. UP contributes about 8.3% to the country's GDP as per Reserve Bank of India (RBI).

There are two types of GSDP, nominal and real. Nominal GSDP is calculated based on the current market prices whereas real GSDP is computed based on constant (fixed) prices. A base year is fixed by the government for determining constant prices, which change after a fixed period, usually 5 or 10 years. To analyze GSDP concerning night time luminosity, consistent GSDP data referring to one base year is required. The GSDP data for the years 2004-2017 consists of GSDP evaluated according to two base prices (2004-05 and 2011-12). To eliminate the inflation and realize the actual growth of the economy, we have projected the GSDP of the years calculated with 2011-12 base price to 2004-05 base prices. In other words, conversion of nominal to real GDP using GDP deflator (Das et al., 2007) [Equation (1) & (2)].

$$GDPDeflator = \frac{NominalGDP}{RealGDP} \times 100 \quad \text{—(1)}$$

$$Real\ GDP = \frac{Nominal\ GDP}{GDP\ Deflator} \times 100 \quad \text{—(2)}$$

Since GSDP doesn't quantify the value added by the environment or doesn't differentiate between expenditure on good or bad things, there have been objections (Ghosh et al., 2013). Hence, a few other factors have been taken into consideration.

3.3.2. Power.
The capability to produce and make electricity available to one and all is one of the most important concerns of a country. The availability of electric power directly impacts the development of various other economic sectors. Reliable and affordable power ensures the growth of the economy as a whole. India is the third-largest producer as well as consumer of electricity. As of 2021, India has an installed capacity of 386.88 GW (Kumar & Sharma, 2019). UP being the most populous state, was a poor electricity consumer until 2017. To revive the electricity distribution companies (DISCOM), in 2015 the government launched the Ujjwal DISCOM Assurance Yojana (UDAY) scheme to improve the operational efficiency of the companies (Electricity Sector Reform in Uttar Pradesh, 2018). The state government has been promoting development like the building of Jewar international airport, electrification schemes, envisioning UP as a global electronics hub, etc to boost business and employment opportunities (IBEF, 2021). This study uses the per capita availability of power in UP. The Ministry of Statistics and Programme Implementation (MOSPI) publishes a report 'Energy Statistics' every year, from which the yearly UP power and energy data has been aggregated.

3.3.3. Energy.
It can be consumed in the form of renewable resources such as wind, hydropower, solar, etc, or majorly used non-renewable resources such as coal, natural gas, petroleum, etc. The launch of the 'Saubhagya- Sahaj Bijli Har Ghar Yojana' in 2017 assured rapid rural electrification (Kumar & Sharma, 2019), a government initiative to provide electricity in the most rural and remote regions of the country. A significant increase in electrification was noticed from 1.28 lakhs in 2017 to almost 2.49 lakhs in 2021 in UP. Nighttime light imagery can be used as a proxy indicator in confirming the reported statistics. With a population of 1.39 billion in India, the Statistical Review of World Energy reported energy consumption of about 31.98 exajoules (8883.33 TWh) (BP Global, 2021). Here we review the total energy consumption by the ultimate consumers in Uttar Pradesh. The statistical is extracted from Energy Statistics reports available on MOSPI's platform.

3.3.4. Education.
It is a social development indicator and is considered a means to ensure economic growth. It has been argued that education is a basic means that can help humans escape starvation and poverty and thus improve the quality of life an individual leads (Burchi, 2006). The literacy rate in India is steadily increasing at the rate of 1.5% per year and currently stands at 73%. According to census 2011, about 67.7% of the population is literate in UP. In this study, we chose the total number of schools, total enrolment in school, and percentage of schools having access to electricity. National Institute of Educational Planning and Administration(NIEPA) developed a Unified District Information System for Education (UDISE) software to aggregate all the district, state, and national level education data on the platform for further planning and analysis. They publish a yearly educational report, from which UP education data has been obtained.

3.3.5. Birth rate.
It is the number of humans born per thousand people in a given period. UP contributes to the highest birth rate in urban areas (22.8) and the second-highest in rural areas (27.3) in India (Census of India Website : SRS Statistical Report, 2018). Since the population statistics are available after every decade, the birth rate can be associated with the change in population up to a certain extent. This helps in observing how the change in the size of the population reflects in the NTL imagery.

4. Methodology

Four consistent long-term NTL data products for the years 2004-2017 have been used in this study. The flowchart of the procedure is explained in Figure 4.

(1) For extraction of UP from the globally harmonized Set A and B, a QGIS tool 'Clip Raster by Mask Layer' and a vector mask layer of UP are used for clipping. This tool extracts the cells of the raster that lie within the boundaries of the input vector mask layer.

(2) 'Zonal Statistics' calculates the Sum of Lights (SOL) for each raster file. This tool computes the statistics, in this case, the sum of the radiance values within the extent of UP. For each dataset, SOL for all years is calculated and compiled for further analysis.

(3) GSDP is rebased to 2004-2005 base prices using GDP deflation and yearly socio-economic statistics for UP are aggregated. A relationship between the SOL of each dataset and each factor is tested in R Studio using regression analysis. Mathematically, the regression line can be expressed as;

$$y = \beta_0 + \beta_1 x + \varepsilon \qquad (3)$$

where y is the dependent variable (socio-economic factor), x (SOL) is the independent variable, $\beta_0$is the intercept, $\beta_1$is the coefficient and ε is the residual.

(4) The accuracy of the regression model is evaluated using the R-squared coefficient of regression. The R^2 value ranges between 0-1 and indicates the model performance. The higher the R^2 value the better is the fit and model prediction.

5. Results and Discussions

The accuracy of the simulation of the four annual sets is analyzed by studying the statistical relationship between their SOL values and the mentioned socio-economic indicators.

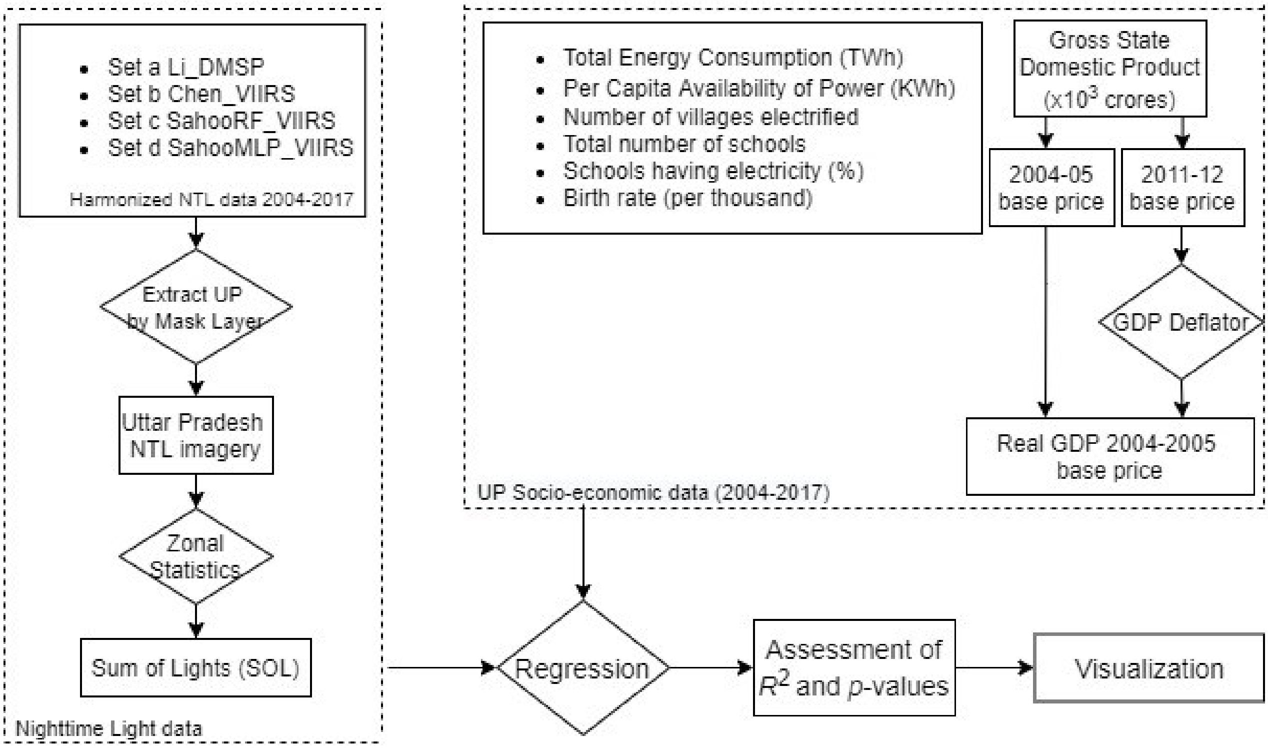

Figure 4. Flowchart: Analysis of socio-economic factors w.r.t SOL values of four consistent 2004-2017 datasets

5.1. Evaluation of different harmonized products for estimation of GSDP, Energy Consumption and Available Power

Figure 5(d) illustrates a strong positive correlation between Set D (R2=0.902) VIIRS annual composite. This signifies VIIRS night time light MLP as an excellent supplementary measure for the prediction of GSDP. Upon comparison of other VIIRS-like datasets w.r.t GSDP, a weak positive correlation is observed. It is noted that NTL using DMSP-like product (Figure 5 (a)), with a moderate to strong correlation (R2=0.802) can also be used for forecasting the state GDP.

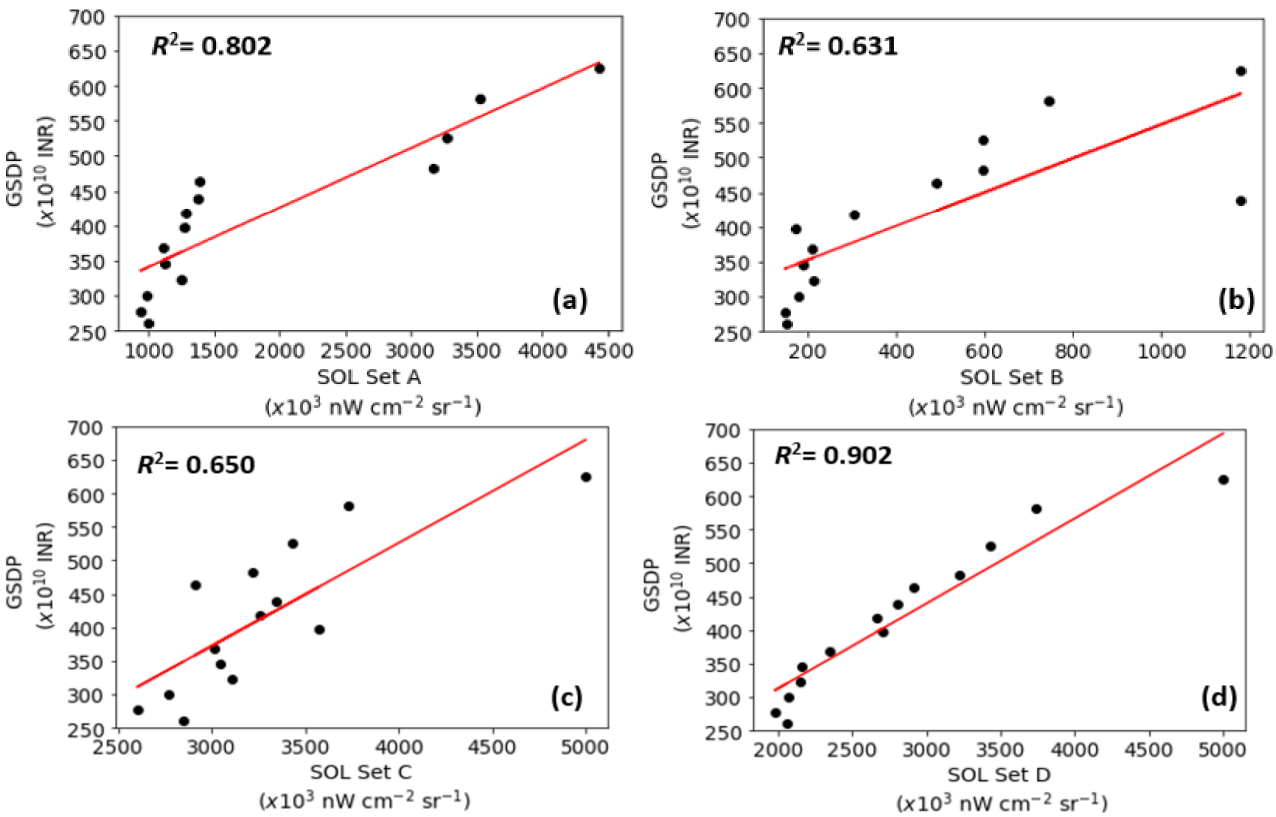

Figure 5. Relation between GSDP and SOL derived from (a) Set A, (b) Set B, (c) Set C, (d) Set D

There exists a strong correlation between the state GDP and Total Energy Consumption (R^2=0.970) as well state GDP and Per Capita Availability of Power (R^2=0.974)as depicted in the scatter plots in Figure 6 and 7 respectively. Hence, these factors will follow a similar trend w.r.t SOL for all the datasets.

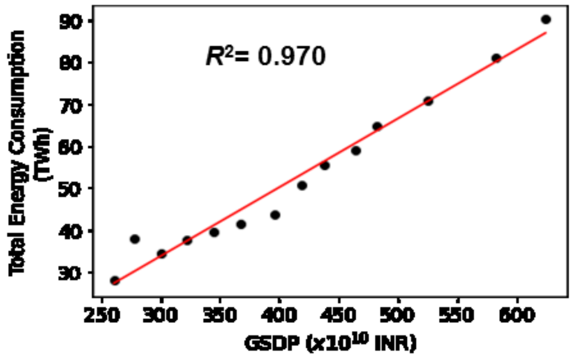

Figure 6. Relation between GSDP with Energy

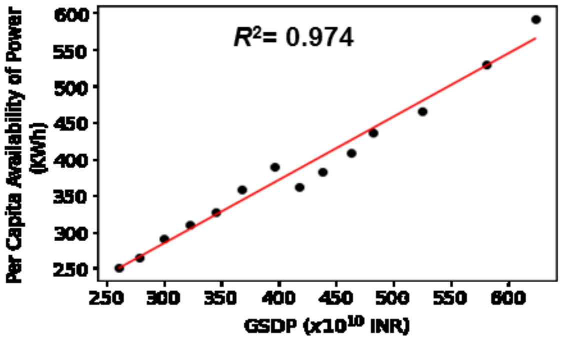

Figure 7. Relation between GSDP and Power

5.2. Evaluation of different harmonized products for estimation village electrification

As we observe from the scatterplots in Figure 8, the regression line shows a poor fit of all types of SOL datasets with the number of villages having a supply of electricity. The plots suggest that night time imagery is not fit to use to predict the number of areas having electricity. The total SOL value might increment on an annual basis, but it may not help us in quantifying the number of villages electrified.

5.3. Evaluation of different harmonized products with educational indicators

To predict the percentage of schools electrified every year in UP, Set D-VIIRS products exhibit the best results (R^2=0.781) as shown in Figure 9. The calibrated long-term Set A-DMSP product also shows a good fit (R^2=0.773) and can be used to forecast the schools being electricity connection every year.

As per records, many new schools open in UP. Upon evaluating the association of the number of schools with the percentage of schools having access to the supply of electricity, we see a strong correlation (R^2=0.773). It is to be noted that this may be indicative of the fact that apart from the existing schools being electrified,the new schools being developed are more developed and are already equipped with electricity connections. This may have been possible due to the government initiatives pushing the availability of power for all. Initially, the total number of students enrolled in schools was also considered in the study, which could hint at economic growth to a certain extent. However, it is a statistically insignificant factor as per our evaluation using T-tests

5.4. Evaluation of different harmonized products with the birth rate

On examining the scatterplots in Figure 11, we can see a moderate negative correlation between SOL and Birth rate. The Set D products represent a better link between SOL and birth rate as compared to all other products.

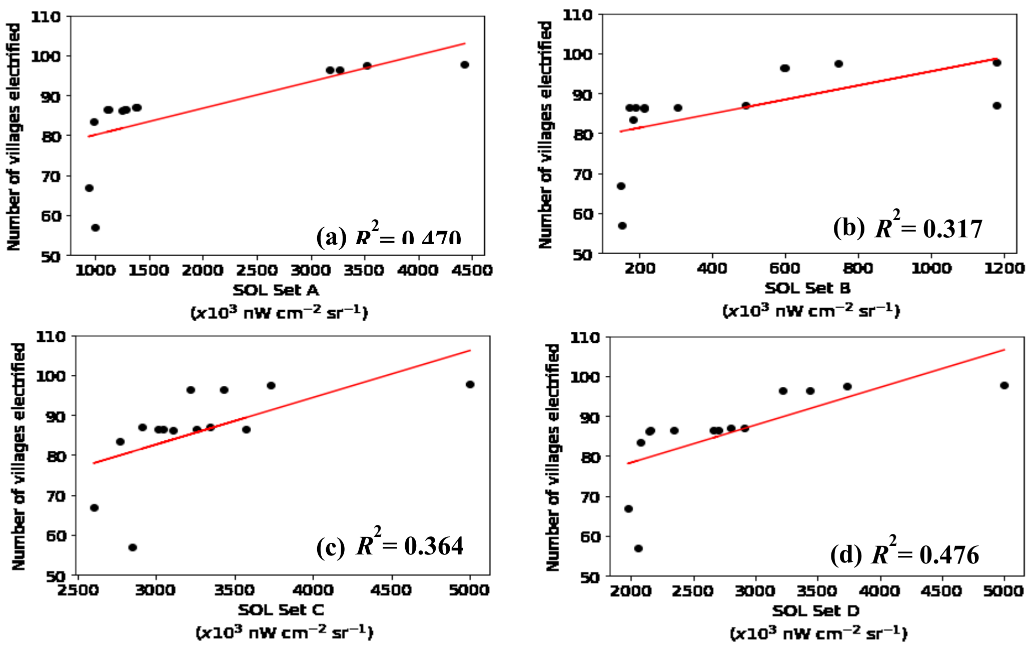

Figure 8. Relation between Number of villages electrified in UP and SOL derived from (a) Set A, (b) Set B, (c) Set C, (d) Set D

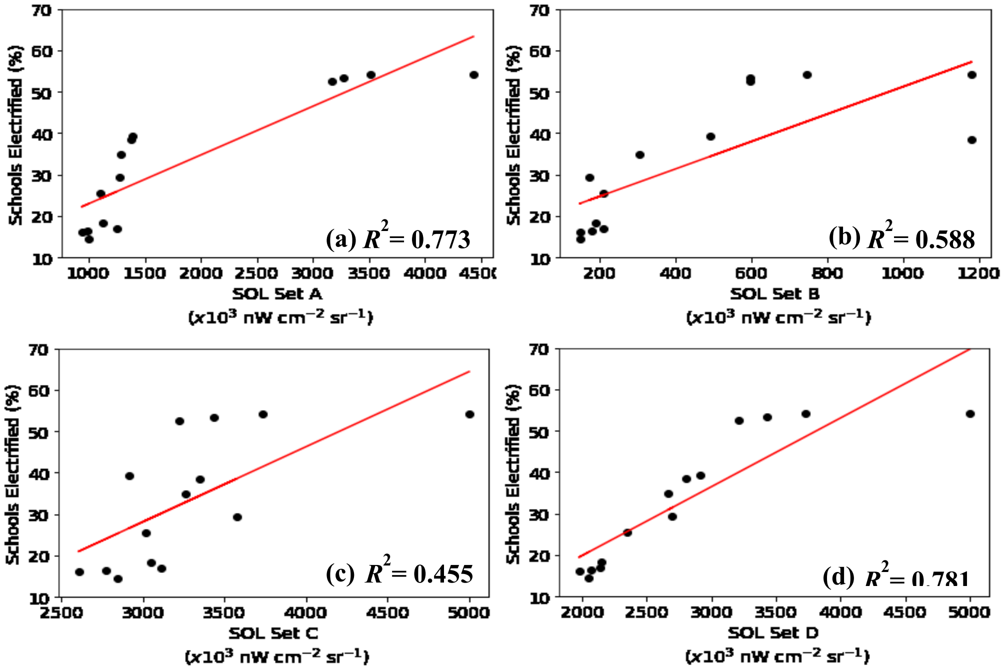

Figure 9. Relation between Percentage of schools electrified in UP and SOL derived from (a) Set A, (b) Set B, (c) Set C, (d) Set D

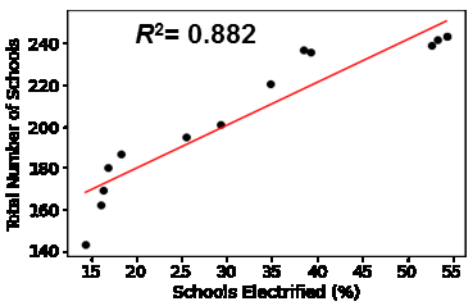

Figure 10. Relation between Number of Schools and Schools Electric Supply

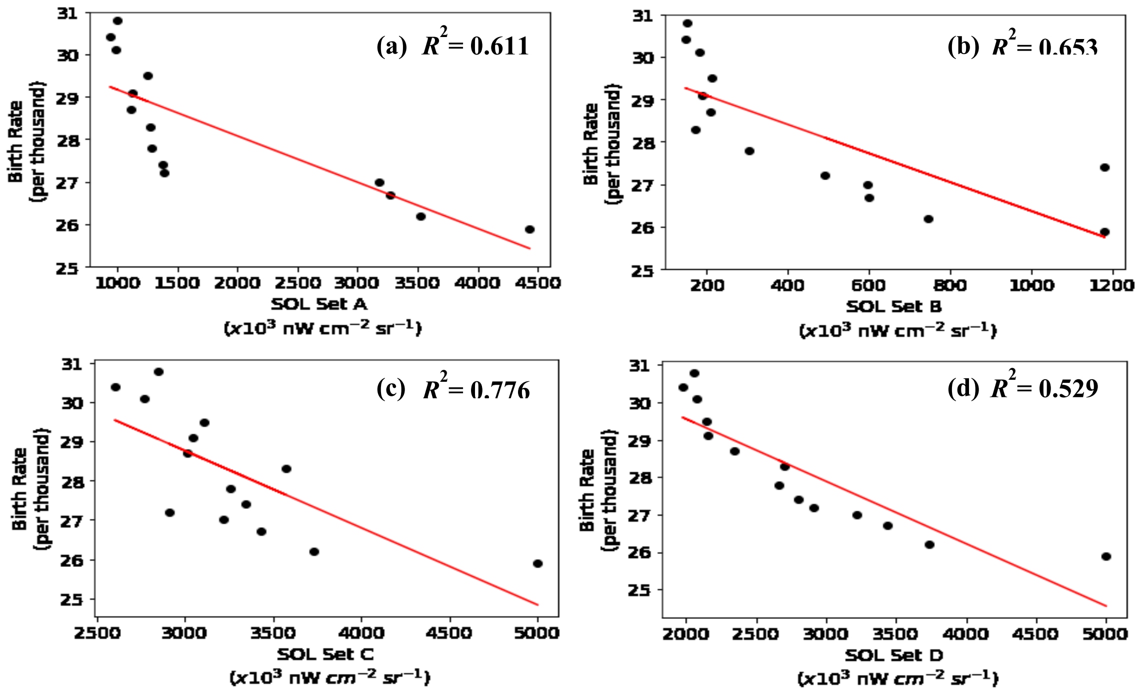

Figure 11. Relation between Birth Rate of UP and SOL derived from (a) DMSP-like Set A, (b) VIIRS-like Set B, (c) VIIRS-like Set C, (d) VIIRS-like Set D

6. Conclusion

Socio-economic studies reveal the true status of a region in terms of its population, employment, urbanization and wealth. Although several inter-calibration studies state the relative importance of night time light datasets to be used as a proxy for socioeconomic factors, evaluation of these substitutes is equally important. This study evaluates four such inter-calibrated SOL products. The results obtained from regression analysis of the different inter-calibrated SOL products and various socio-economic factors firstly indicate careful evaluation of NTL imagery as a substitute for predicting the factual status of social and economic development. Secondly, our analysis clearly shows that the VIIRS-like Set-D dataset gives better correlation results with all the indicators considered, other than village electrification. It is inferred that regional-scale studies perform better using NTL datasets harmonized using the Multi-layer Perceptron technique. Set-B and Set-C fare poorly in the regional level comparisons. Therefore, the methodology adopted for inter-calibration highly affects the socio-economic factor estimation. Other techniques of calibration can be explored by researchers in the future. This analysis help decision-makers in making informed decisions and enable researchers in selecting appropriate data for their studies.

Acknowledgements

This study is part of M.Tech course carried out by the first author. Thanks to the Director, Indian Institute of Remote Sensing, Indian Space Research Organization (ISRO), Dehradun, India for his support. Sincere thanks to Earth Observation Group, Payne Institute for Public Policy at CSM for producing and providing night-time satellite datasets to the scientific community.

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