# USING VIIRS NIGHTTIME IMAGE IN ESTIMATING GROSS STATE DOMESTIC PRODUCT FOR INDIA AND ITS COMPARISON WITH ESTIMATIONS FROM THE DMSP-OLS RADIANCE-CALIBRATED IMAGE

Tilottama Ghosh[1], Christopher D. Elvidge[2], Kimberly Baugh[1], Feng Chi Hsu[1], Mikhail Zhizhin[1, 3]

1: Cooperative Institute for Research in Environmental Sciences, 216 UCB, University of Colorado Boulder, Boulder, CO 80309, USA; Email: tilottama.ghosh@noaa.gov; kim.baugh@noaa.gov, feng.c.hsu@noaa.gov

2: Earth Observation Group, NOAA National Centers for Environmental Information, Boulder, CO 80305 USA; Email: chris.elvidge@noaa.gov

3: Space Dynamics and Mathematical Information Processing, Space Research Institute of the Russian Academy of Sciences, Moscow 117997, Russia. Email: mikhail.zhizhin@noaa.gov

**KEY WORDS:** Nighttime lights, official Gross State Domestic Product, Predicted economic estimates

**ABSTRACT:** The use of Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS) nighttime stable lights and radiance-calibrated images for the estimation of socio-economic variables at different administrative levels is well established. The onset of low light imaging data collection by the Suomi National Polar-Orbiting Partnership Visible Infrared Imaging Radiometer Suite (SNPP VIIRS) since October, 2011, which are of superior spectral and spatial resolution compared to DMSP-OLS, have stimulated further interest in the use of nighttime images as proxy variables for socio-economic research. In this paper, we conduct a comparative study between the relationships of the Sum of Lights (SOL) extracted from the 2015 VIIRS Nighttime Lights annual composite, and the DMSP-OLS radiance-calibrated image of 2010, and official Gross State Domestic Product (GSDP) for the respective years for India. Logarithmic models show a better predictive relationship between the SOL and GSDP for both the years. In fact, the results indicate that the coefficient of determination ($R^{2)}$ derived from regressing the SOL extracted from the radiance-calibrated image of 2010 with the official GSDP of 2010 is slightly higher (0.04 or 4%) than that derived from regressing the SOL extracted from the 2015 VIIRS nighttime image and the GSDP of India for 2015. A discussion is ensued deliberating on the two different types of nighttime images used in this study. Moreover, residual maps were made to evaluate the merit of the SOL derived from the DMSP-OLS image of 2010, and the VIIRS image of 2015 to serve as proxy variables for GSDP.

## 1. INTRODUCTION

The Indian economy is the fourth largest growing economy in the world according to the World Bank's latest edition of Global Economic Prospects. In the year 2017, India's economy is expected to advance 7.2% (Mourdoukoutas, 2017). Economic growth measures how much more an economy produces in comparison to a prior period, and this comparison removes the effects of inflation. Gross Domestic Product (GDP) is the most accepted measure of economic growth. It measures the monetary value of the final production of good and services within a nation's geographic borders over a specified period of time (Amadeo, 2017).

Compiling GDP of nations is an extremely complicated process involving several data series and numerous sources. As economies get rich there is a shift from agriculture, and manufacturing to services. Quantifying the outputs of services, such as, hospitals, banks, universities, and law firms is challenging. The outputs in most cases are over-stated or under-estimated. GDP underestimates the benefits of innovation, especially if it is a rapid one. The Boskin Commission in 1996 concluded that the U.S. real GDP growth had been underestimated by about 1.3 percentage points because of the inability to keep up with the adjustment for innovation in consumer electronic goods, especially computers. Moreover, during the times of rapid innovation there occurs a gap between market price paid (which is used to calculate GDP) and what a consumer would be willing to pay for the product (called consumer surplus in economics). GDP measures only include expenditure on goods and services, and thus exclude anything that is 'free.' There are copious services which are available online for free – Google, Wikipedia, open source software, news and entertainments sites, music, films, and podcasts. For these goods, the consumer surplus reaches a maximum. There are quite a few categories of GDP for which statisticians have to formulate prices because market prices do not exist, for example, government expenditure, informal economy in developing countries, household work for which no payment is given. The complex network of the global economy, both in terms of the variety of products and services, has only added to the complication of measuring GDP, and are inadequate in providing a complete picture of the global trade statistics. GDP cannot measure economic wellbeing, or provide an answer to the question of sustainability, or study the impact of economic growth on environmental indicators (The Economist, 2016). Therefore, developing alternative measures of GDP is imperative.

The value of the nighttime satellite images as a proxy of economic measures such as GDP has long been realized and implemented in several studies. (Ghosh et al., 2010; Chaturvedi et al. 2011; Li et al. 2013; Henderson et al., 2014; Shi et al. 2014; Zhou et al., 2015; Dai et al., 2017)

## 2. DATA

### 2.1 Nighttime lights imagery

Two types of nighttime images were used to calculate the sum of light intensity values in this paper with the objective of assessing which one provides a better estimate of economic activity of the states of India. The first one is the Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS) radiance-calibratedimage of 2010, and the second one is the annual Suomi National Polar-Orbiting Partnership Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) of 2015, flown jointly by NASA and NOAA. Both these datasets are downloadable for free from NOAA Earth Observation Groups' website https://www.ngdc.noaa.gov/eog/.

The DMSP-OLS annual global cloud-free stable lights products have been produced since 1994, and there is a consistent dataset available from 1992 to 2013. However, the stable lights data were produced from data collected at high gain settings, resulting in sensor saturation on brightly lit areas, for example, city centers. This has been one of the major limitations of stable lights data. To overcome this shortcoming, the radiance-calibrated data were developed. For making these products DMSP-OLS visible band data were collected at three fixed-gain levels – low, medium, and high. In fixed-gain mode the radiances were calculated based on preflight sensor calibration. This made it possible to collect unsaturated data on all detectable lights, and greatly expanded the dynamic range of the final cloud-free composite (Hsu et al., 2015). Ziskin et al. (2010) refined the method by adding a ramped weighting scheme to level out the discontinuities in the gain setting switch zones. In addition, the stable lights products of the corresponding years were blended in to supplement the limited number of fixed gain collections. Hsu et al. (2015) further worked on this to create a time series of radiance-calibrated nighttime lights products covering all years for which fixed-gain data were collected, and also performed intercalibration of the products. For this study, the latest available annual radiance-calibrated nighttime image that of F16 2010 was used. The units of the data are in W $cm^{-2}$ $sr^{-}1$. The spatial resolution of the data is 30 arc seconds, which is approximately $1km^2$ at the equator.

The second kind of low-light imaging data which was used in this study is the annual VIIRS DNB data of 2015. The DNB data detects electric lighting from human settlements. The VIIRS DNB data provides significant improvement over the DMSP-OLS data, comprising 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 (Miller et al., 2012; Elvidge et al., 2013a; Miller et al., 2013). There are a series of steps involved in creating the annual VIIRS DNB data. This includes, excluding background noise, solar and lunar contamination, data affected by cloud cover, and removing features unrelated to electric lighting (for example, fires, flares, and volcanoes). The VIIRS DNB annual product which has been used in this paper has the biomass burning and portions of aurora filtered out, and also has all the background noise removed. The data are in floating point values and the units are average radiances in nW $cm^{-2}$ $sr^{-1}$. The spatial resolution of the data is 15 arc seconds (Elvidge et al., 2017).

Both these nighttime lights data products span from 75°N to 65°S. These nighttime images are referenced by latitude/longitude World Geodetic System (WGS 1984) coordinates. These images need to be corrected for area, as the cell areas are largest at the equator and smallest at the poles. This correction was done using the area grid provided along with the LandScan population database of LandScan, Oak Ridge National Laboratory (LandScan, 2016). The area raster dataset contains areas of 30 arc second cells. The units of the areas are in square kilometers. The DMSP radiance-calibrated grid was multiplied with the area grid for getting area-corrected DMSP radiance-calibrated data of 2010. The area grid was resampled to 15 arc seconds and then multiplied with the VIIRS nighttime image of 2015 for deriving area-corrected VIIRS nighttime image.

The gas flares are detected in the VIIRS nightfire products (Elvidge et al., 2013b). Polygons were hand drawn on these detections to create the 'polygon mask', which was used to mask out the gas flares from both the nighttime light products.

After the completion of these pre-processing steps, the study area of India (38°N, 68°E, 6°N, 98°E) was carved out from the DMSP radiance-calibrated image of 2010, and the VIIRS nighttime image of 2015 (Figures 1 and 2).

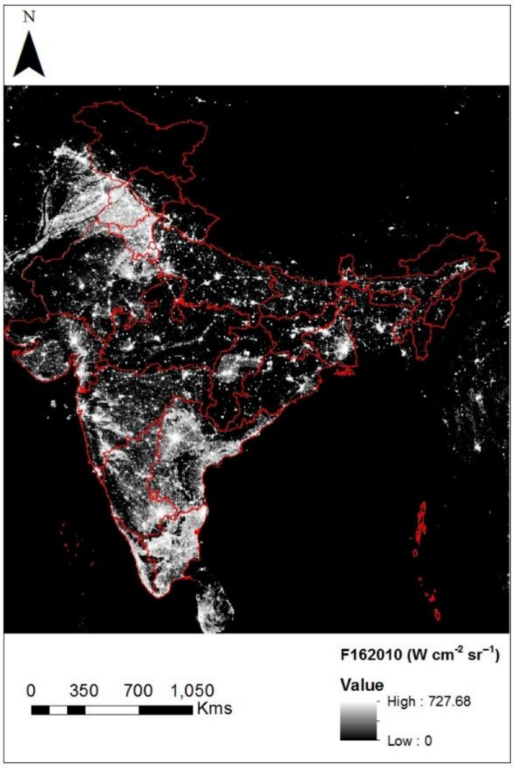


Figure 1. DMSP-OLS Radiance-calibrated image of 2010

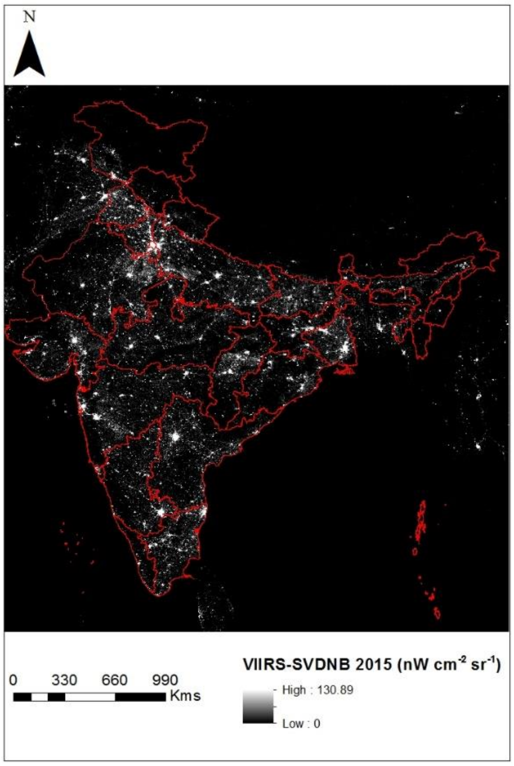


Figure 2. SNPP-VIIRS annual image of 2015

**2.2 Gross Domestic Product data for the states of India (GSDP)**

The Gross State Domestic Product (GSDP) data for the states of India was retrieved from two sources. The 2010-11 GSDP data at constant prices (with the base year of 2004-05) was derived from the website of Statistic Times (Ministry of States and Program Implementation, 2015). Constant series was selected instead of current series of economic data as it adjusts for the effects of price inflation, and measures the true growth of an economic series (The World Bank). The data were in crores of rupees. GSDP data were not available for the Union territories of Lakshadweep, Dadra and Nagar Haveli, and Daman and Diu. They were converted to billions of rupees (by dividing by 100). Further, the data were converted into Purchasing Power Parity (PPP) U.S. dollars keeping in mind the need for comparison with data of other countries in future studies. The PPP figure makes international comparisons possible, as it attempts to address the fluctuations in country exchange rates by expressing the quantity of goods and services each currency can buy locally as one dollar would buy in the U.S. (Ghosh et al., 2010). The PPP conversion factors for 2010, 2014, and 2015, Local Currency Unit (LCU) per international dollar were derived from the World Bank's website (The World Bank). Thus, the data for 2010-11 were in billions of PPP U.S. dollars.

The GSDP data for 2014-15, and 2015-16 for the states of India were derived from the Government of India's data repository (GOI, 2017). These GSDP data were in constant prices with the base year being 2011-12. GSDP data were not available for the Union territories of Lakshadweep, Dadra and Nagar Haveli, and Daman and Diu. For states which did not have GSDP data for 2015-16, the data for 2014-15 were used. The data were in lakhs of rupees, and were converted to billions of rupees (by dividing by 10,000). These data were also converted to PPP U.S. dollars using PPP conversion factor got from World Banks' website.

**2.3 Shapefiles of the states of India**

Shapefiles for the 28 states and 6 Union territories (UT) of India were taken from the data repository of a former premier economic research firm, Indicus Analytics. Indicus had derived this vector data from Navteq/Nokia Here vector boundary data of 2013. The twenty-ninth state of India, Telangana, was formed on 2nd June, 2014. For the ease of comparison between data extracted from the nighttime images of 2010 and 2015, Telangana was not considered as a separate entity even when extracting data from the nighttime image of 2015.

## 3. ANALYSIS

The shapefile for the states of India was overlaid on the DMSP radiance-calibrated nighttime image of 2010 and the VIIRS nighttime image of 2015 and the Sum of Lights (SOL) value of the states and UT were extracted. The sum of lights is the sum of the light intensity values of all pixels within the boundaries of every state or UT of India. Figure 3 showing the SOL for the states of India for 2010 illustrate that the southern states of India (except Kerala), the western states of Gujarat and Rajasthan, and the northern state of Uttar Pradesh are brighter compared to the northern and eastern states of India. In fact, the north-eastern states of India- Arunachal Pradesh, Nagaland, Manipur, Mizoram, are some of the dimmest states. The map of the SOL of 2015 (Figure 4) gives a similar picture, only that, Madhya Pradesh is included in the brightest quantile class of states.

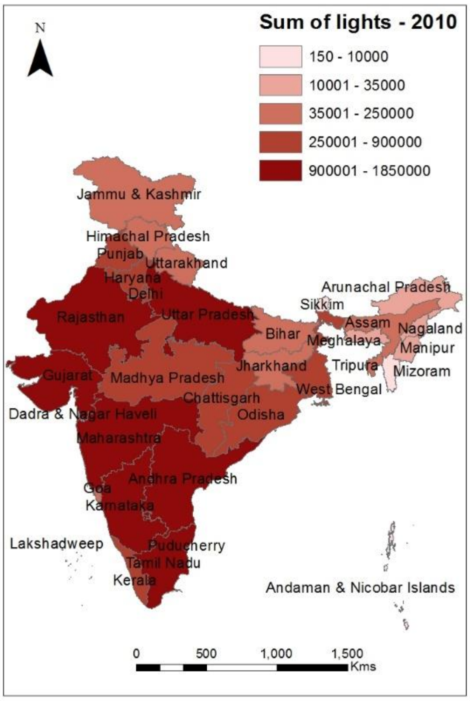


Figure 3. Sum of Lights for 2010

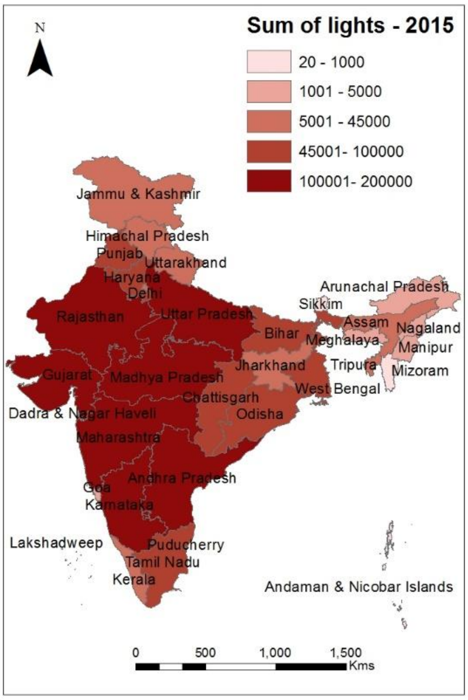


Figure 4. Sum of Lights for 2015

Figures 5 and 6 show the GSDP of the states of India in PPP U.S. dollars. Similar GSDP class intervals were taken for the two maps to show how much the states have become richer over the period of four or five years that is from 2010-11 to 2014-15, and 2015-16. Besides the overall maximum GSDP increasing from $522 billion for Maharashtra to $900 over this period of time, most of the states, except for Punjab, Haryana, Madhya Pradesh, West Bengal, and the north-eastern states, have had an increase of GSDP, and have moved up to the next class of GSDP values.

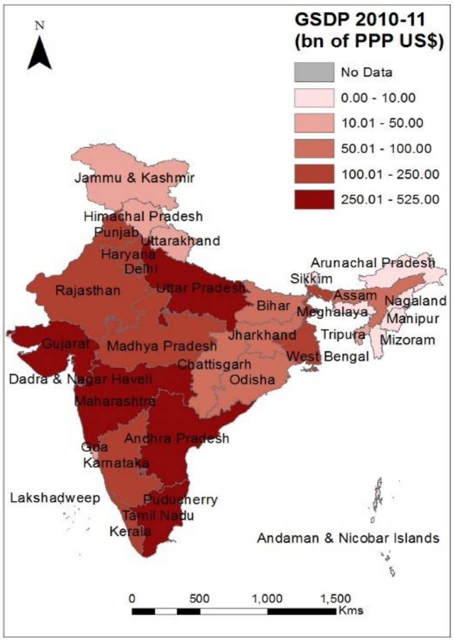


Figure 5. GSDP of Indian states – 2010-11

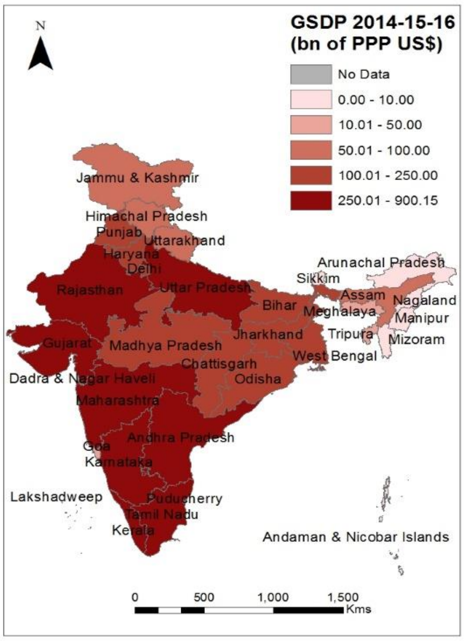


Figure 6. GSDP of Indian states – 2014-15, 2015-16

A simple linear regression scatter plot of the Sum of Lights (SOL) of the DMSP radiance-calibrated image of 2010 against the GSDP values of 2010-11 (Figure 7) shows that these variables are positively correlated and, provides a coefficient of determination ($R^2$) value of 0.80. Some states are shown to be outliers. Maharashtra, for instance, seems to be much wealthier than what is represented by the SOL value. On the other hand, Andhra Pradesh, Rajasthan, and Karnataka, seem to be much brighter than what is represented by their GSDP values. The regression analysis between the VIIRS 2015 SOL and the official GSDP values of 2014-15, and 2015-16 again shows that these two variables are positively correlated, and provides a coefficient of determination ($R^2$) value of 0.76 (Figure 8). In this figure too, Maharashtra is an outlier, as its GSDP value is higher compared to the SOL value. Tamil Nadu is also shown as an outlier as it has higher GSDP in comparison to its SOL value. Interestingly, both Andhra Pradesh and Karnataka, which were shown to be below the line of best fit for 2010 were seen to be above and close to the line of best fit in 2015. This indicates that their economic position as represented by their GSDP values had improved over the course of five years, and the growth in their GSDP values were almost commensurate with their SOL values. Rajasthan, however, continued to be much brighter although economically poorer as represented by its GSDP value. Uttar Pradesh and Madhya Pradesh were also outliers in Figure 8 as they both had higher SOL values in comparison to their economic positions as represented by their GSDP values.

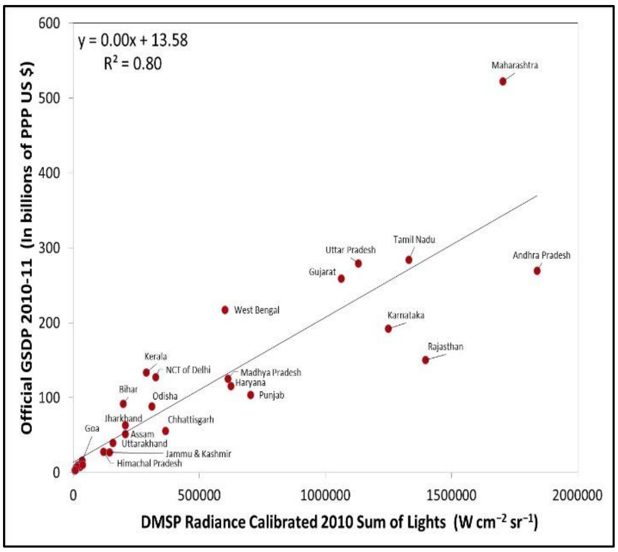


Figure 7. Regression analysis between SOL and GSDP-2010

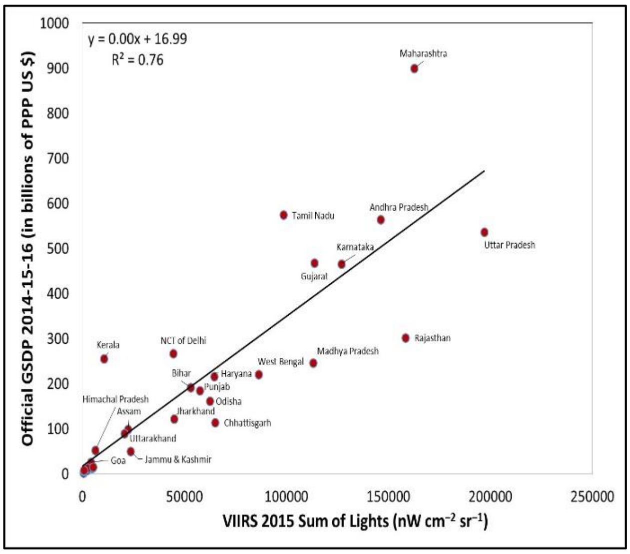


Figure 8. Regression analysis between SOL and GSDP- 2015

Figures 7 and 8 also show the two variables; SOL and GSDP of the states have a non-linear trend. Thus, a log-log model was developed for these two variables, for both 2010 and 2015. Taking the natural log of the SOL and GSDP on the X axis and Y axis, respectively, for 2010, in Figure 9, the coefficient of determination; $R^2$ was pushed up to 0.96. The natural logarithmic equation (Equation 1) is given as -

$$\ln(GSDP) = 0.83 * \ln(SOL) - 6.18 \quad (1)$$

And, the equation can be interpreted as a one percent increase in the SOL is associated with a 0.83 percent increase in the GSDP, on average. The result is statistically significant with a p-value <0.0001. Again, in Figure 10, taking the natural log for both SOL and GSDP, the coefficient of determination was pushed up to 0.92, and the equation is given as –

$$\ln(GSDP) = 0.84 * \ln(SOL) - 3.88 \quad (2)$$

and, can be interpreted as a one percent increase in the SOL is associated with a 0.84 percent increase in the GSDP, on average. The result is statistically significant with a p-value <0.0001. It is also noticed in Figure 10 that Kerala is an outlier indicating that Kerala is much dimmer in comparison to its GSDP value.

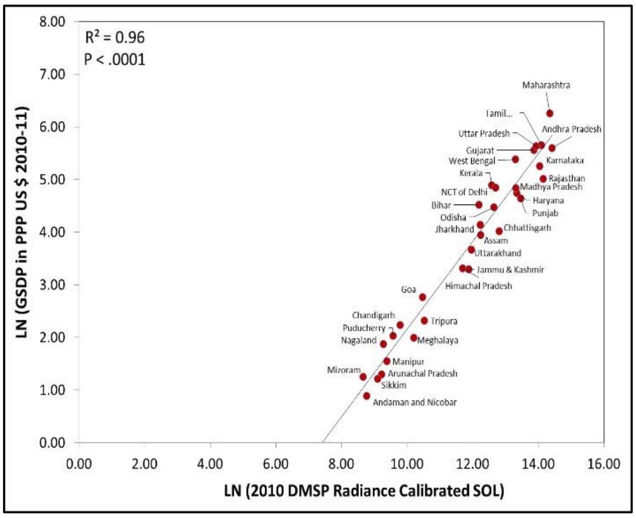


Figure 9. Logarithmic Regression analysis between SOL and GSDP-2010

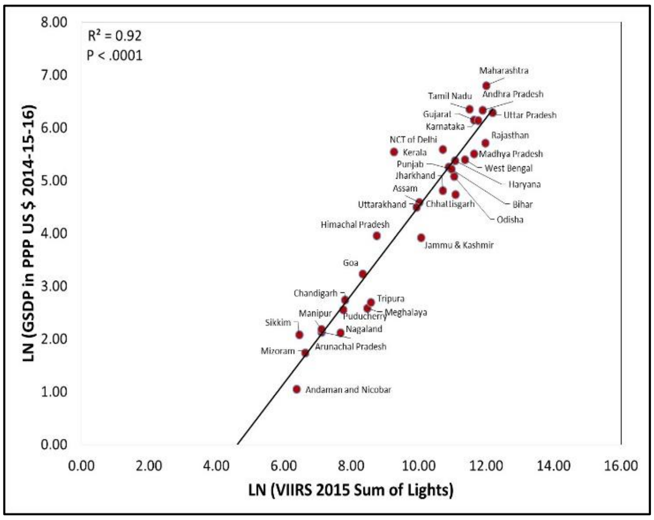


Figure 10. Logarithmic Regression analysis between SOL and GSDP- 2015

In order to understand the goodness of the logarithmic models in predicting GSDP, the exponents were taken for both the logarithmic models, and the estimated GSDPs were computed for both 2010 and 2015 (Equations 3 and 4).

$$\text{Estimated (GSDP2010)} = \text{Exponential}\,(0.83 * \ln(SOL) - 6.18) \quad (3)$$

$$\text{Estimated (GSDP2015)} = \text{Exponential}\,(0.84 * \ln(SOL) - 3.88) \quad (4)$$

After computing the estimated GSDPs for 2010 and 2015, the residual percentages were computed (Equation 5).

$$\text{Residual GSDP \%} = \frac{\text{Official GSDP} - \text{Estimated GSDP}}{\text{Official GSDP}} \times 100 \quad (5)$$

Figure 11 shows the residual percentage map of GSDP for the states of India for 2010. It is seen that GSDP was overestimated by more than 45% for the states of Jammu and Kashmir, Punjab, Rajasthan, and Chhattisgarh, with the largest overestimation (82%) for Rajasthan. It was underestimated by more than 25% for the states of Maharashtra, Kerala, West Bengal, Bihar, Nagaland, and the UT of NCT of Delhi. Figure 12 shows the residual percentage map of GSDP for the states of India for 2015. It is seen that GSDP was overestimated by more than 45% for the states of Jammu and Kashmir, Rajasthan, and Chhattisgarh (similar to Figure 11), and also added the north-eastern states of Nagaland, Meghalaya, Tripura, and the Andaman and Nicobar Islands. The greatest percentages of overestimation were for the states of Chhattisgarh (94%) and Jammu and Kashmir (90%). GSDP was underestimated by more than 25% for the states of Maharashtra, Kerala, Tamil Nadu, Sikkim, Himachal Pradesh, and the UT of NCT of Delhi.

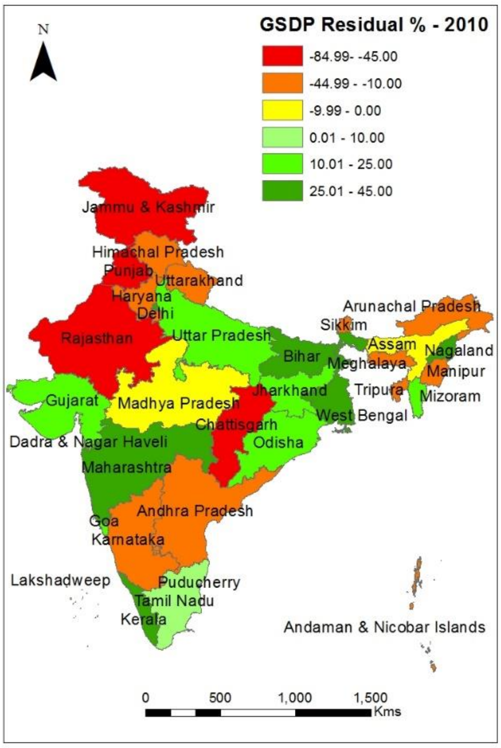


Figure 11. GSDP Percentage Residual Map-2010

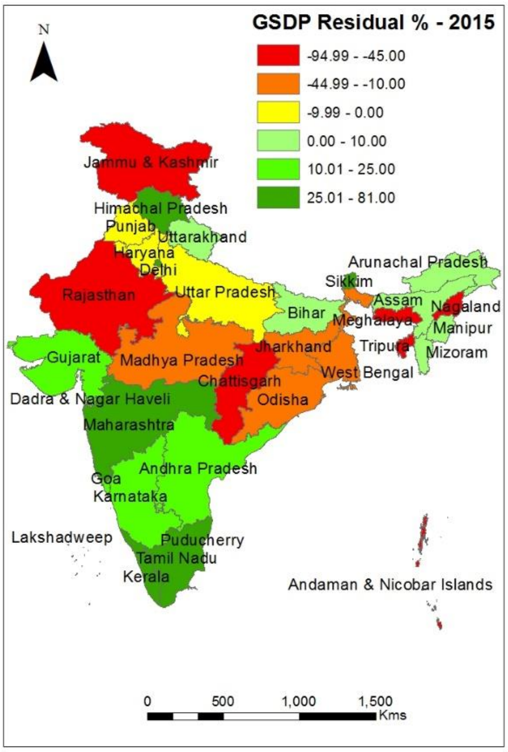


Figure 12. GSDP Percentage Residual Map-2015

## 4. DISCUSSION

Two types of nighttime image was used in this analysis with an objective of evaluating which one provides a better estimate of GSDP at the state level for India. Examining the simple linear regression models for the years 2010 and 2015 showed that the relationship between these variables have a non-linear trend. Thus, a logarithmic model was developed for both of the years, 2010, and 2015.

In case of both the simple linear regression model and the logarithmic model it was seen that the DMSP radiance-calibrated nighttime image of 2010 provided slightly better $R^2$ in estimating the GSDP of 2010, than the VIIRS 2015 nighttime image did in estimating the GSDP of 2015. However, just on the basis of a difference of coefficient of determination value of 0.04 or 4 % (0.96-0.92) it is not possible to unequivocally declare that the radiance-calibrated nighttime lights are superior to the VIIRS nighttime image.

There are a couple of things to consider when comparing these two images from two different points of time. The VIIRS nighttime image is indisputably superior in terms of its spatial and spectral resolution, having lower detection limits, having on-board calibration, and no saturation in urban cores. The DMSP radiance-calibrated image, on the other hand, were created by blending in fixed gain data with the stable lights data for only a few years for which the data were made available (1996, 1999, 2000, 2003, 2004, 2006, 2010, and partial 2011). Only the blending in of fixed gain data could help to overcome the urban core saturation problem of the DMSP data. In addition, the DMSP data are no longer being produced after 2013 because of the orbital degradation over time. And, the 2010 radiance-calibrated data is the last one which is available for a full year.

Another major difference between the two nighttime images is the overpass time. The overpass time for DMSP is in the early part of the evening, near 19:30. In contrast, the overpass time of the Suomi National Polar-orbiting

Partnership (SNPP) VIIRS is after midnight, near 1:30. Although it is believed that highest lighting is usually observed before 22:00 hours in urban areas, and there is a decline in urban lighting, inspection of VIIRS DNB data has shown that plenty of lighting is detected even after midnight (Elvidge et al., 2013a). Nonetheless, the different overpass times are something that should be taken into consideration when comparing these two sets of data.

Additionally, there is the uncertainty related to the official GSDP data itself. All the ambivalence associated with national accounts data has been discussed before in this paper and in several other literature (Ghosh et al., 2010; Chaturvedi et al. 2011; Li et al. 2013; Henderson et al., 2014; Zhou et al., 2015; Dai et al., 2017). The national accounts data for India can be looked upon with the same suspicion. Thus, running a regression of the SOL with the official GSDP data is only another attempt at developing a proxy measure for economic estimates. It is an attestation to the statement that several error-prone measures are better than one, especially if there is no reason to think that the measurement errors are correlated (Rao, 1992).

On the whole, the logarithmic models developed using SOL and GSDP for both the years 2010 and 2015 does a satisfactory job in estimating GSDP. It is seen that in the logarithmic model for 2015 (Figure 10), the state of Kerala is an outlier, in that, its GSDP value is higher than the SOL value. Only hypothetical questions can be raised to answer this – Do the people of Kerala turn off their lights sooner (before 1:30 am) than the other states? Kerala is the leading state of India on many accounts. It has the highest literacy rate and the highest Human development Index (HDI) (Wikipedia). Could the highly educated population be more aware of conserving electricity and power? Also, Kerala had witnessed a significant emigration of population to the Arab states in the 1970s and early 1980s, and its economy has been greatly dependent on the inflow of remittances from this expatriate community (News 18, 2007). Thus, although these remittances add to the state GSDP, it does not increase the SOL value. By excluding Kerala from the logarithmic model in Figure 10 the $R^2$ value increases to 0.95, and is almost as good as the logarithmic model developed with the radiance-calibrated nighttime image (Figure 9).

The residual map of 2010 (Figure 11) shows an overestimation of GSDP for the states of Jammu and Kashmir, Punjab, Rajasthan, and Chhattisgarh. The state of Rajasthan is brightly lit along the border districts with Pakistan, although the area of the Thar Desert is dark. The bigger cities of Rajasthan are also brightly lit, and may have contributed to the overall brighter lights of the state in comparison to its GSDP. Punjab has many affluent farmers who have the highest share in income, consumption and investment in the country (Kishore, 2017). These rich farmers may have contributed to the substantial amount of lighting in these states (Chaturvedi et al., 2011). The brightly lit cities of Jammu and Kashmir along its south-western border with Pakistan might have contributed to the bright lighting in Jammu and Kashmir in comparison to its GSDP, and thus caused its GSDP to be overestimated. The central part of Chhattisgarh is brightly lit, which includes all the bigger cities and could have caused the overestimation of GSDP from lights. Lights underestimate GSDP (Figure 11) by more than 25% in the states of Maharashtra, Kerala, West Bengal, Bihar, Nagaland, and the UT of NCT of Delhi. The states of Maharashtra, West Bengal, and the UCT of New Delhi have the largest metropolitan cities in India – Mumbai, Kolkata, and Delhi (Businessworld, 2017), and the lights are not able to capture the economic affluence of these states in terms of their GSDP. The state of Kerala has a lot of remittance flowing in from its expatriate population which adds to the GSDP value of the state, but is not reflected in the lights. Bihar is one of the most densely populated states of India (Census 2011), and the lights are perhaps unable to capture the contribution of this population to the GSDP of the state.

Figure 12 showing the residual map of GSDP for the state of India for 2015 shows a similar pattern of overestimation of GSDP for the states of Jammu and Kashmir, Rajasthan, and Chhattisgarh. In addition, the north-eastern states of Nagaland, Meghalaya, Tripura, and the UT of Andaman and Nicobar Islands are added. One explanation for the overestimation of GSDP for the north-eastern states and the Andaman and Nicobar Islands could be that the VIIRS 2015 image with a higher spatial and spectral resolution is enabling much more lights to be captured than the DMSP image of 2010, and causing an overestimation. Figure 12 shows underestimation of more than 25% for the states of Maharashtra, Kerala, Tamil Nadu, Sikkim, Himachal Pradesh, and the UT of NCT of Delhi. Maharashtra, Tamil Nadu, and UT of NCT of Delhi again house the wealthiest cities of India – Mumbai, Chennai, and Delhi, respectively, and the lights are not completely able to capture this affluence. The underestimation of GSDP of Kerala can be explained with the similar reason as for Figure 11.

## 5. CONCLUSION

In this paper we have explored which nighttime image – the DMSP-OLS radiance-calibrated nighttime image of 2010 or the SNPP VIIRS nighttime image of 2015 provides better estimates of Gross State Domestic Product (GSDP) of the Indian states. On the basis of logistic regression results between the Sum of Lights (SOL) extracted from both the nighttime images and the official GSDP data for both the years, it is seen that the coefficient of determination obtained from the logistic regression analysis between the radiance-calibrated nighttime image of 2010 and GSDP values of 2010 is 0.04 or 4% higher. However, both of the logistic regression analysis provides high $R^2$ values – 0.96 for 2010 and 0.92 for 2015, and the results are statistically significant. In addition, it proves that both these nighttime images can serve as suitable proxy measures for GSDP data for developing countries like India.

The radiance-calibrated nighttime image of 2010 was the last full year of this type of image that was produced. Since we have the radiance-calibrated images of 1996, 1999, 2000, 2003, 2004, 2006, and for partial year for 2011, these can be used to do a time-series analysis for GSDP growth over the years. And, from April 2012 onward till recent times, we have the SNPP VIIRS monthly nighttime images, which will enable to extend the analysis further. The SNPP VIIRS is unquestionably spectrally and spatially superior to the DMSP-OLS nighttime images, and since it has on-board calibration the data are comparable over the years. Thus, using the DMSP-OLS radiance-calibrated images and the SNPP VIIRS images it will be possible to study economic growth of developing countries such as India. Obviously, it is necessary to examine the relationship between nighttime images and economic variables for other countries, and also at finer spatial resolutions. But in all, the DMSP-OLS radiance-calibrated nighttime images and the SNPP VIIRS images serve as promising substitutes for economic variables.

## REFERENCES


Amadeo, K., 2017. What is Economic Growth? Retrieved September 14, 2017, from https://www.thebalance.com/what-is-economic-growth-3306014.

Businesssworld, 2017. Richest Cities of India, Retrieved September 15, 2017, from http://businessworld.in/article/Richest-Cities-Of-India/28-06-2017-121011/

Census, 2011. Density of India, Retrieved September 15, 2017, from http://www.census2011.co.in/density.php.

Chaturvedi M., Ghosh, T., Bhandari, L., 2011. Assessing income distribution at the district level for India using nighttime satellite imagery. Proceedings of the 32nd Asia-Pacific Advanced Network Meeting, New Delhi, India.

Dai, Z., Hu,Y., Zhao, G., 2017. The suitability of different nighttime light data for GDP estimation at different spatial scales and regional levels. Sustainability, 9, 305.

Elvidge, C. D., Baugh, K., Zhizhin, M., Hsu. F.C., 2013a. Why VIIRS Data are superior to DMSP for mapping nighttime lights. Proceedings of the Asia-Pacific Advanced Network, East-West Center, University of Hawai'i – Manoa, pp. 62-69.

Elvidge, C. D., Zhizhin, M., Hsu. F.C., Baugh, K., 2013b. VIIRS nightfire: satellite pyrometry at night. Remote Sensing, 5, pp. 4423-4449.

Elvidge, C.D., Baugh, K., Zhizhin, M., Hsu, F.C., Ghosh, T., 2017. VIIRS night-time lights. International Journal of Remote Sensing, 38(21), pp. 5860-5879.

Ghosh, T., Powell, R., Elvidge, C.D., Baugh, K.E., Sutton, P.C., & Anderson, S., 2010. Shedding light on the global distribution of economic activity. The Open Geography Journal, 3, pp. 147-160.

Government of India. Retrieved September 14, 2017, from https://data.gov.in/catalog/gross-state-domestic-product-constant-prices

Henderson, J.V., Storeygard, A., Weil, D.N., 2014. Measuring economic growth from outer space. American Economic Review, 102(2), pp. 994-1028.

Hsu, F.C., Baugh, K. E., Ghosh, T., Zhizhin, M., Elvidge, C.D., 2015. DMSP- OLS radiance-calibratednighttime lights time series with intercalibration. Remote Sensing, 7, pp. 1855-1876.

Kishore, R, 2017, Have Punjab's Rich Farmers Created Their Own Nemesis?, Retrieved September 15, 2017, from http://www.livemint.com/Opinion/O9pTj3bLdTV0MzDGYTuHlK/Have-Punjabs-rich-farmers-created-their-own-nemesis.html.

LandScan Population Database, Oak Ridge National Laboratory, Retrieved October 6, 2016, from http://web.ornl.gov/sci/landscan/

Li, X., Xu, H., Chen, X., Li, C., 2013. Potential of NPP-VIIRS nighttime light imagery for modeling the regional economy of China. Remote Sensing, 5, pp. 3057-3081.

Ma, T., Zhou, C., Pei, T., Haynie, S., Fan, J., 2014. Responses of Suomi-NPP VIIRS derived nighttime lights to socioeconomic activity in China's cities. Remote Sensing Letters, 5:2, pp. 165-174.

Miller, S.D., Mills, S.P., Elvidge, C.D., Lindsey, D. T., Lee, T.F., Hawkin, S.J. D., 2012. Suomi satellite brings to light a unique frontier of environmental sensing capabilities. Proceedings of the National Academy of Sciences of the United States of America, 109 (39), pp. 15706–15711.

Miller, S. D., Straka III, W., Mills, S. P., Elvidge, C.D., Lee, T.F., Solbrig, J., Walther, A., Heidinger, A. K., Weiss, S. C., 2013. Illuminating the capabilities of the Suomi NPP VIIRS Day/Night Band. Remote Sensing, 5 (12), pp. 6717–6766.

Ministry of States and Program Implementation, 2015, Retrieved September 14, 2017, from http://statisticstimes.com/economy/gdp-of-indian-states.php

Mourdoukoutas, P., 2017. Modi's India the World's 4th Fastest Growing Economy, Retrieved September 14, 2017, from https://www.forbes.com/sites/panosmourdoukoutas/2017/06/22/modis-india-the-worlds-4th-fastest-growing-economy/#54be4f4120ae.

News 18, 2007. Keralites, Largest Indian Expat Community in the UAE, Retrieved September 15, 2017, from http://www.news18.com/news/india/keralites-largest-indian-expat-community-in-uae-276779.html

Rao, B. L S. P., 1992. Identifiability in Stochastic Models. Academic Press, New York.

Shi, K., Yu, B., Huang, Y., Hu, Y., Yin, B., Chen, Z., Chen, L., Wu, J., 2014. Evaluating the ability of NPP-VIIRS nighttime light data to estimate the Gross Domestic Product and the electric power consumption of China at multiple scales: a comparison with DMSP-OLS data. Remote Sensing, 6, pp. 1705-1724.

The Economist, 2016. The Trouble with GDP, Retrieved September 14, 2017, from https://www.economist.com/news/briefing/21697845-gross-domestic-product-gdp-increasingly-poor-measure-prosperity-it-not-even.

The World Bank. Retrieved September 14, 2017, from https://datahelpdesk.worldbank.org/knowledgebase/articles/114942-what-is-the-difference-between-current-and-constan

The World Bank. Retrieved September 14, 2017, from https://data.worldbank.org/indicator/PA.NUS.PPP

Wikipedia, Retrieved September 14, 2017, from https://en.wikipedia.org/wiki/Kerala

Zhou, Y., Ma, T., Zhou, C., Xu, T., 2015. Nighttime light derived assessment of regional inequality of socioeconomic development in China. Remote Sensing, 7, pp. 1241-1262.

Ziskin, D., Baugh, K., Hsu, F.C., Ghosh, T., Elvidge, C.D., 2010. Methods used for the 2006 radiance lights. Proceedings of the Asia-Pacific Advanced Network Meeting, Hanoi, Vietnam.