ANALYSIS OF SNPP-VIIRS-DNB DERIVED NIGHTLIGHTS OVER INDIA

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ABSTRACT: Nightlight observations from satellites are being used by researchers for nearly three decades to monitor the societal development. Nightlight images available from Day/Night Band (DNB) of Visible Infrared Imaging Radiometer Suite (VIIRS) aboard the Suomi-National Polar-orbiting Partnership (SNPP) satellite have many advantages over the previously available images from Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS). This study aims at analyzing the SNPP-VIIRS-DNB images over India at sub-national scale, taking nightlights as proxy to monitor the development. Monthly average radiance composite images from SNPP-VIIRS-DNB made available by the Earth Observation Group of NOAA are used to prepare annual (April to March) average radiance composite images for 2012-13 and 2016-17. While preparing the annual composites, outliers due to ephemeral events (if any) are removed taking number of cloud-free observations in each month as the weighting factor. To suppress the background values, we used three approaches: (i) thresholding based on observed radiances of inland water bodies, snow, desert and ocean; (ii) subtracting minimum value through a moving window; and (iii) *Getis statistic*. However, these approaches did not yield good results. Finally, "sum of lights" (SOL) are calculated from annual average radiance images of 2012-13 and 2016-17 and plotted for the States and Union Territories (UT) of India. Most of the States/UT and India as a whole show increase in nightlight as expected; whereas, some of the northern and north-eastern States show decrease in nightlights. The plausible reasons for the decrease are: (i) errors introduced during pre-processing while generating monthly composites and (ii) varying snow cover which affects the background light and hence the SOL value. We conclude that the VIIRS-NTL images are useful in studying the development even at sub-national scale; however, local land cover/ practices need to be considered while interpreting them.

1. INTRODUCTION

The United States Air Force Space Command started a program called Data Acquisition and Processing Program (DAPP) in 1962 to study weather systems and cloud cover. It carried on-board a visible to near infrared imaging system (0.4 - 1.1 μm), called the Operational Linescan System (OLS), which was capable of detecting dim lights (Croft, 1973) using photo-multiplier tubes from an altitude of about 850 km. The scientific community was able to use OLS data when the program was declassified and renamed as Defense Meteorological Satellite Program (DMSP). As the data were not available in digital form, few research papers were published on possible applications of this data in monitoring urban population and energy consumption (Welch, 1980). Since 1992, the Earth Observation Group (EOG) of National Oceanic and Atmospheric Administration (NOAA) has produced time-series of stable nighttime lights (NTL) data which have been pre-processed to remove clouds and other temporary light sources. A slew of research papers followed (most of which are reviewed by Huang *et al.*, 2014), which focused on wide range of applications ranging from population dynamics to the effects of war and natural disasters on NTL. Several studies have shown that nightlights can be a robust indicator of socio-economic growth (Chen *et al.*, 2011; Doll *et al.*, 2006). NTL data have also been used by researchers for estimating demographic parameters and development in the Indian region (*e.g.*, Joshi *et al.*, 2011; Bhandari and Roychowdhury, 2011; Roychowdhury *et al.*, 2011, 2012; Pandey *et al*., 2013). However, DMSP data products have well-known issues such as (i) low spatial (2.7 km) and radiometric (6 bit) resolutions, (ii) no on-board and inter-satellite calibration, and (iii) light saturation and blooming effect.

With the launch of the Suomi-National Polar-orbiting Partnership (SNPP) satellite in 2011 carrying the Visible Infrared Imaging Radiometer Suite (VIIRS) on-board, NOAA-EOG has now shifted its focus of developing NTL data sets from DMSP/OLS to Day/Night Band (DNB) of VIIRS. The data generated from VIIRS/DNB is far superior to its predecessor (DMSP/OLS), both in terms of spatial (742 m) and radiometric (14 bit) resolutions (Elvidge *et al.*, 2013). Studies on monitoring anthropogenic activities using VIIRS/DNB data are also being published (Roman *et al.*, 2015; Bennett *et al.*, 2017).

This study aims at analyzing the SNPP-VIIRS-DNB images over India at sub-national scale, taking nightlights as proxy to monitor the development. We prepare annual average radiance composite images from publicly available monthly average radiance data, and analyze them for all the States and Union Territories (UT) of India.

2. STUDY AREA

The Indian sub-continent is taken as the study area. India is a large South Asian country with about 3.28 M km^2 geographic area and varied topography. There are 29 States and 7 UT's as shown in Figure 1. India has a developing economy whose Human Development Index (HDI) has grown from 0.428 in 1990 to 0.624 in 2015 (UNDP, 2016). It is imperative to quantify this development and understand the regional growth patterns for proper resource management.

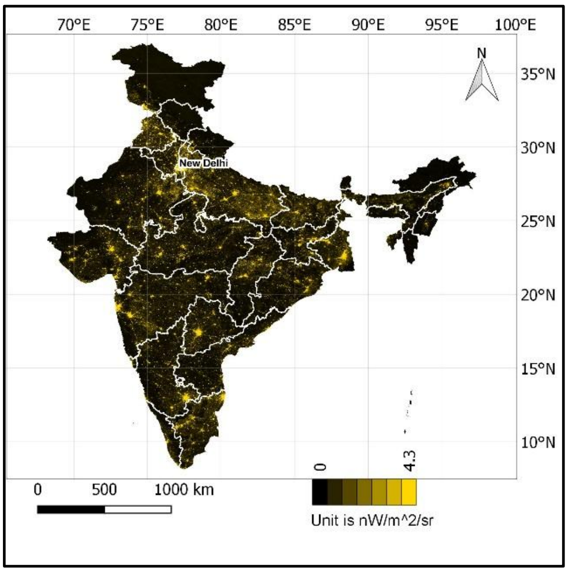

Figure 1: Study area (VIIRS image of March, 2017 is in the background)

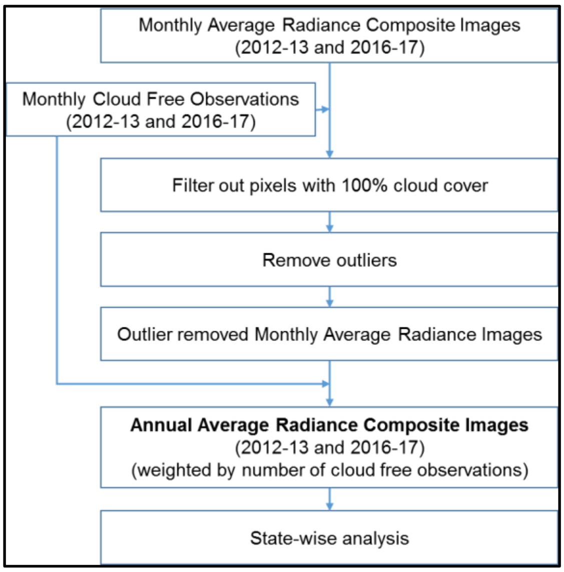

Figure 2: Methodology used in the study

3. DATA

The EOG, National Centers for Environmental Information (NCEI) (formerly National Geophysical Data Center, NGDC), NOAA have processed (file format conversion, geolocation, mosaicking, filtering, compositing) the VIIRS- DNB data and have made available on its website (EOG, 2017). The version-1 monthly composites at 15 arc-second spatial resolution, from April 2012 to March 2013 and April 2016 to March 2017 are used in this study. The "vcm" configuration files are used in which no stray-light correction procedure is applied to ensure high quality data with minimal data changes. EOG provides a set of two geotiff files for each monthly dataset; the monthly stable average radiance values (in nanoWatts/cm^2/sr) and the number of cloud-free observations (NCO) that are used in preparing the monthly average radiance images. The VIIRS-DNB sensor performs on-board calibration and hence these data do not suffer from problems such as saturation, blooming etc. and can detect very low lights (in order of ~2×10^{-11} Watts/cm^2/sr).

4. METHODOLOGY

The version-1 series of monthly composites do not correct for ephemeral (temporary) lights. The sources could be from large “lighted” public gatherings, fires, boats and other temporal lights. Since the nighttime overpass is around 01:30 hours, camp fires and other such non-permanent light sources are not expected to contaminate the NTL dataset. A methodology is formulated in this study to account for such anomalies and generate annual stable lights datasets, as shown in Figure 2.

The computations are carried out using the IDL programming language and QGIS is used for composition of maps. For each pixel, out of 12 (monthly) values, values which correspond to NCO>0 are considered (let us say ‘n’ values are considered, $n \leq 12$). The values which fall inside the mean ± (3×standard deviation) are only retained (let us say ‘m’ values are retained, $m \leq n$). This is done to remove spikes due to temporary lights. The remaining ‘m’ values are weighted using the NCO count to finally derive the annual composited value for each pixel.

To suppress the background lights, we used three approaches: (i) thresholding based on observed radiances of inland water bodies, snow, desert and ocean; (ii) subtracting minimum value through a moving window; and (iii) *Getis statistic*. However, the results are not found suitable (see results section) and thus are not used. Spurious negative values are removed by thresholding those pixels to zero. Finally, the sum of pixel values (or Sum of Lights, SOL) within the area of interest is calculated to study the development over time.

5. RESULTS AND DISCUSSION

This section is sub-divided into two sub-sections, focusing on results obtained from (i) pre-processing monthly NTL datasets to annual composites, and (ii) State-wise analysis of annual composite images.

5.1 Pre-processing results

During the Indian Summer Monsoon period (June - September), monthly composite images show low count of NCO’s throughout the study area. This led to low radiance values during this period. The algorithm used in this study is able to detect and remove spikes (months with unexpectedly high radiance values). The weighting of radiance values with NCO’s led to averaging of the radiance values to lower than their maximum levels. Table 1 shows the statistics derived from the annual composite images for the two years.

Table 1: Range of values in the annual composite images

Statistic for India	Annual Composite	
	2012-13	2016-17
Minimum	-0.319	-0.595
Maximum	3566.05	6534.73
Mean	0.286	0.335
Standard Deviation	6.419	2.70

On exploratory analysis of the annual composite images, it is found that the range (spread) of values is very large and that unexpected negative values also exist in the data. Further, the mean radiance value of the annual composites is found to improve significantly over time, while standard deviation reduced. The increase in mean radiance implies that overall nightlights in India have increased over time, thus indicating development. It is also observed that some of the areas which were completely dark in 2012-13 NTL image are electrified in 2016-17. This correlates with the data available on Open Government Data (OGD) Platform of India (OGD Website, 2017), which states that the percentage cumulative inhabited village electrified has increased from 94.36% on 2013-03-31 to 99.25% on 2017-03-31 (MoP, 2017a, 2017b). Rural electrification data are also updated regularly on the GARV portal of the Government of India which provides detailed statistics about the status of rural electrification in India (GARV Website, 2017).

To suppress the background light from the NTL images using a uniform cutoff value, several uninhabited sites are selected to explore their radiance values. Table 2 lists the minimum and maximum values in the annual composite images for these sites. It is found that no single cutoff value could serve the purpose of suppressing background light for the entire study area. Also on interactive visualization using different stretching techniques in GIS, it is noticed that even a small cutoff value, like 0.20 nW/cm^2/sr, eliminates valid pixels which are small villages having a source of power.

Table 2: Minimum and maximum values (in nanoWatts/cm^2/sr) at uninhabited sites

North of Badrinath (Uninhabited / Snow)	Min: 0.129 Max: 0.263	Western Rajasthan (Desert)	Min: 0.088 Max: 0.169
Tehri Reservoir (Water body)	Min: 0.49 Max: 0.51	Nagarjuna Sagar Reservoir (Water body)	Min: 0.055 Max: 0.149
Bay of Bengal (Ocean / Water body)	Min: -0.023 Max: 0.09	River Bed in Uttar Pradesh	Min: 0.188 Max: 0.292

Next we attempted second approach for suppressing the background light by subtracting the minimum value through a moving window from all the pixels. Different configurations of moving windows (3×3, 5×5, etc.) are tried. This process subdued the radiance images. It not only reduced the intensity of bright urban centers, but also removed genuine low radiance villages and towns. Hence, this technique also could not be used to suppress the background lights.

Then, we computed *Getis* statistic (Gi*) on the NTL images. The Gi* 'z-score' tells where pixels are clustered spatially, bright (lit) or dark (non-lit) clusters in this case. This technique is used with the presumption that if all the bright (lit) areas are correctly identified by appropriately thresholding Gi* then the remaining areas can be treated as background lights. This technique also, however, did not yield good results.

5.2 Analysis of Annual NTL results

The output of the annual compositing algorithm is thresholded to bring all negative values to zero, followed by clipping of individual States/UT and calculation of SOL values. Figure 3 shows an example of the Uttar Pradesh, the fourth largest State in terms of area (~241,000 km^2) and the largest in terms of population (~200 million, 2011 census). Rapid development in the State can be clearly seen as urban centers have expanded, roads and many of the villages have been electrified from 2012-13 to 2016-17. This correlates well with data from OGD i.e., out of the ~98,000 villages in Uttar Pradesh, the percentage cumulative inhabited villages electrified have increased from 88.92% on 2013-03-31 to 99.99% on 2017-03-31 (MoP, 2017a, 2017b).

Figure 4 shows the overall change in NTL (% change in SOL) for all the States/UT in India. Traditionally under-developed regions show maximum change in SOL from 2012-13 to 2016-17. In general, SOL for India (orange bar) is found to increase by 24.4%, with 14 States/UT above the India average and remaining below the India average. Among all the States/UT, Bihar shows the maximum change in nightlights. The top three best performing largest States (area > 100,000 km^2) are Maharashtra, Uttar Pradesh and Gujarat. The top three best performing smallest states (area < 40,000 km^2) are Lakshwadeep, Andaman and Nicobar Islands and Nagaland.

Decrease in the nightlights are observed in the 8 States (Arunachal, Delhi, Haryana, Himachal Pradesh, Mizoram Punjab, Sikkim and Uttarakhand), which is anomalous. Spatial exploration of the regions shows that several factors could have influenced such a result. Figure 5 shows the zoomed-in portion of Northern India. Punjab and Haryana are wheat producing States where the practice of burning the crop residue is prevalent. By closer examination of the two time-period images for these two States, it is observed that the dim (low-intensity) lights over villages and the overall brightness is appreciably reduced in 2016-17 image as compared to 2012-13 image. We interpret the reduction in the nightlights in 2016-17 in the States of Delhi, Haryana and Punjab is possibly due to over-correction for crop residue burning during pre-processing.

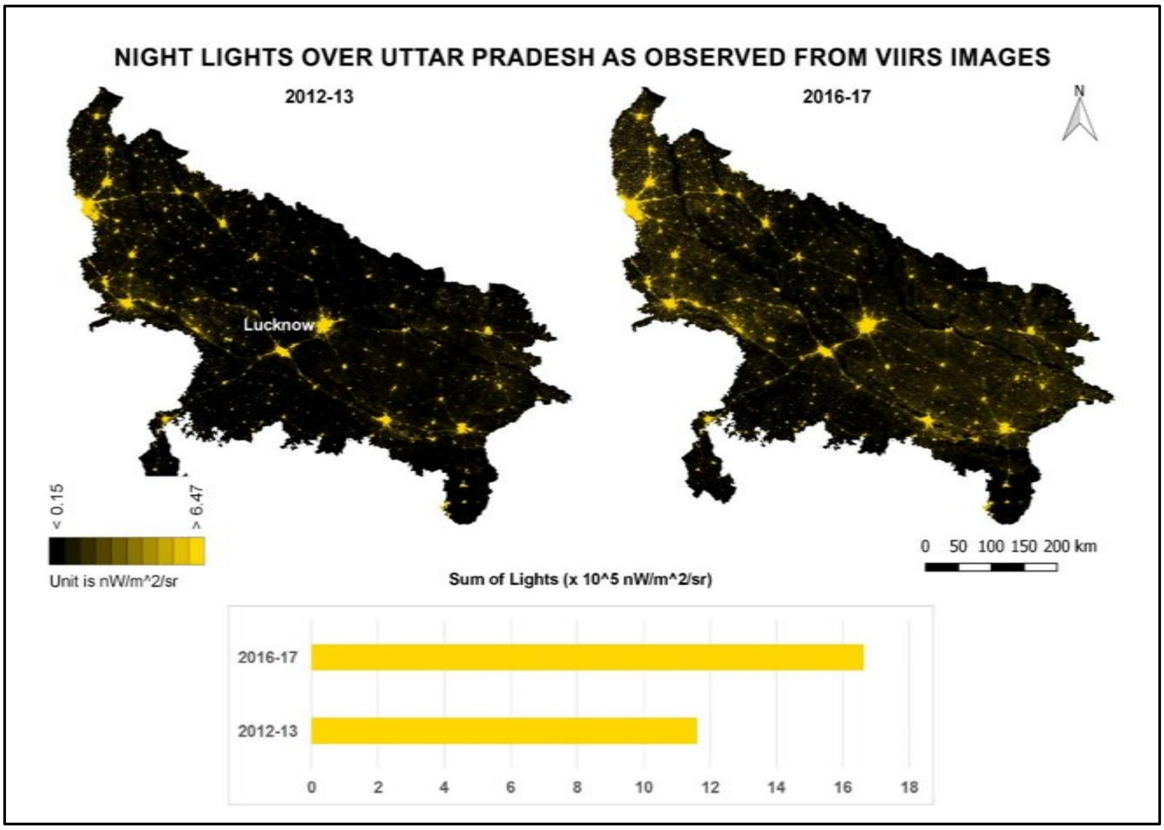

Figure 3: NTL images of Uttar Pradesh for 2012-13 (left) and 2016-17 (right)

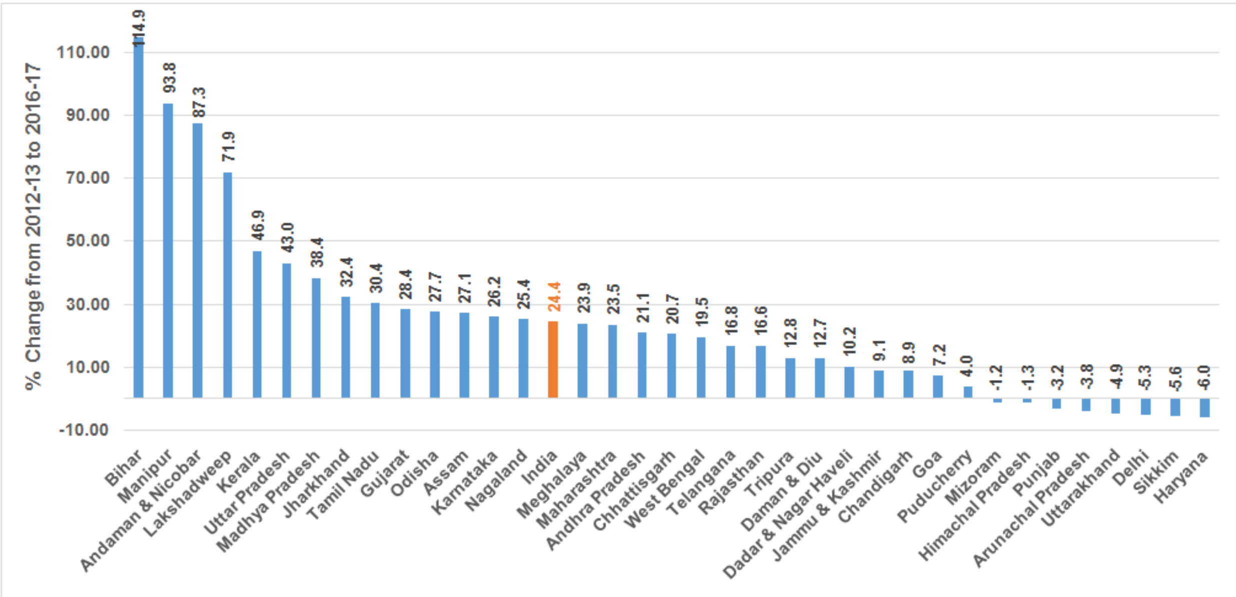

Figure 4: Change in NTL (% change in SOL) from 2012-13 to 2016-17

In case of Uttarakhand, although there are reports of migration of people from the hills to plains but an appreciable reduction in nightlights from 2012-13 to 2016-17 is certainly anomalous. There are two important aspects which need consideration: (i) as Uttarakhand is a hilly State with majority of the land under forest, this area is prone to frequent forest fires, and (ii) the higher reaches are under permanent snow cover. We attribute the reduction in nightlights in 2016-17 in the State of Uttarakhand is possibly due to over-correction for forest fires and also varying snow cover. Temporal change in the extent of snow cover changes the background lights due to high albedo. VIIRS images show very low radiance values even in the snow covered areas, which can affect the SOL values when the radiance values are summed up for the whole State. Same is the case for the State of Himachal Pradesh also.

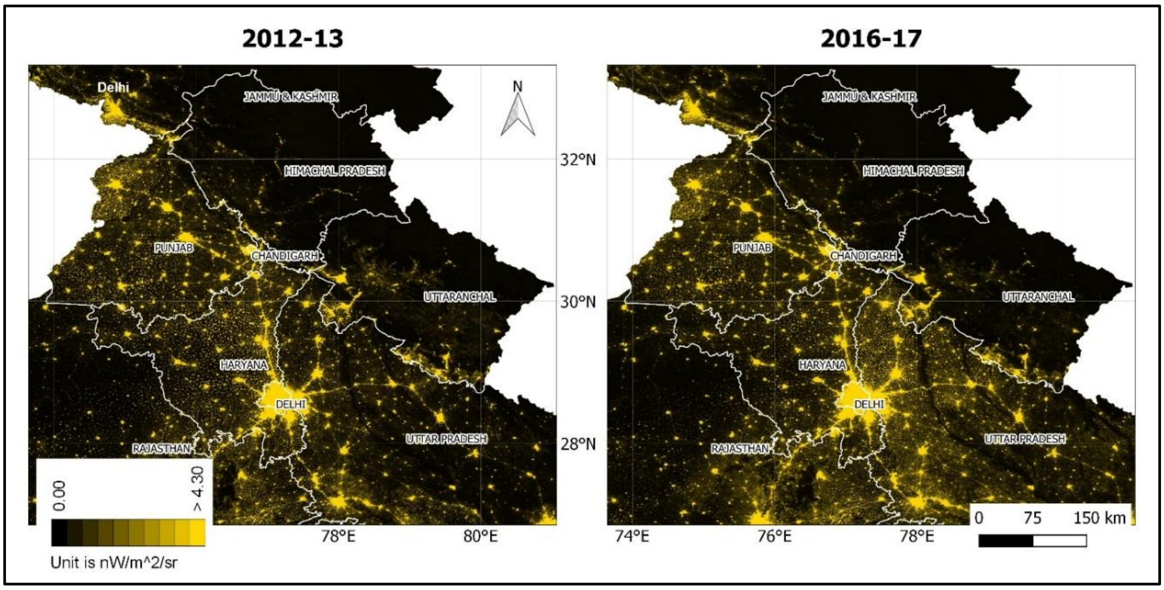

Figure 5: Comparison of annual NTL for Northern India

In the North-Eastern States of Arunachal Pradesh and Sikkim, the reduction in nightlights is possibly due to albedo effect of snow cover. The State of Mizoram shows unexpected high radiances in the south-western part in the 2012-13 annual composite (Figure 6). These areas are densely forested and have no habitation or source of power. Hence, slightly low radiance in 2016-17 as compared to 2012-13 is possibly due to bright artifacts in 2012-13 NTL image introduced during pre-processing while generating monthly composites.

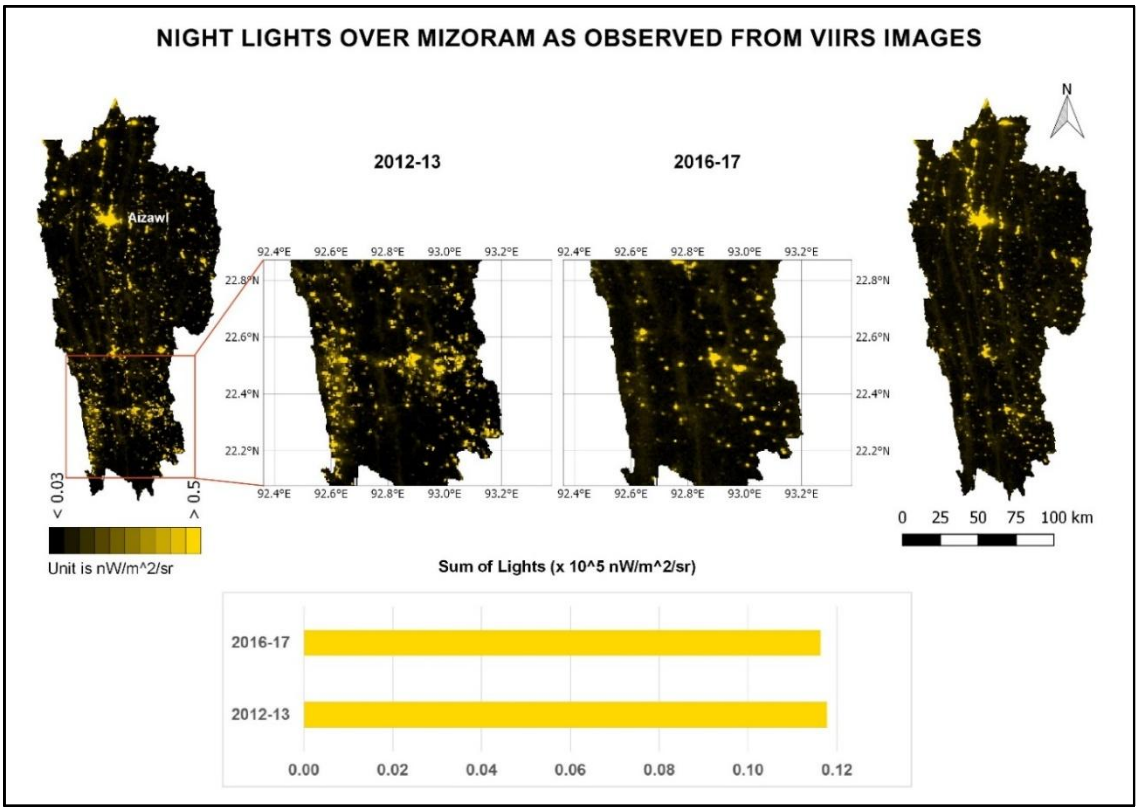

Figure 6: Artifacts in VIIRS NTL data in south-western part of Mizoram

The above observations indicate that the decrease in nightlights over time does not necessarily indicate negative growth/ development. The plausible reasons for decrease in nightlights are: (i) pre-processing errors introduced during generation of monthly composites by EOG-NOAA, particularly while correcting for forest fires or crop residue burning, and (ii) variation in snow cover in the hilly States which causes change in background light due to its high albedo. The errors and artifacts highlighted above need to be corrected before using this dataset as time-series for trend analysis studies. Ancillary spatial information, such as land use practices (crop residue burning, *jhum* cultivation) and land cover of the area (forest, water body, etc.) may also be incorporated into the pre-processing algorithm to minimize such errors.

6. CONCLUSIONS

This study analyses VIIRS NTL images of 2012-13 and 2016-17 over India at sub-national scale. Monthly composites of VIIRS downloaded from EOG/NOAA website are processed to prepare annual average composites which are then analyzed to study the change in nightlights across all the States/UT of India, using SOL metric. The nightlights over India as well as in majority of the States/UT have increased over time; however, an anomalous behaviour (decrease in nightlights) is observed in a few States. Analysis indicates that such an anomalous behavior is possibly due to errors introduced at the time of pre-processing of data while preparing monthly composites by EOG/NOAA and also due to varying background lights of snow cover in the hilly States. It is concluded that VIIRS images can be used for monitoring the human activities even at sub-national scale; however, local land-cover/ practices need to be considered while interpreting the VIIRS images.

7. ACKNOWLEDGEMENTS

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