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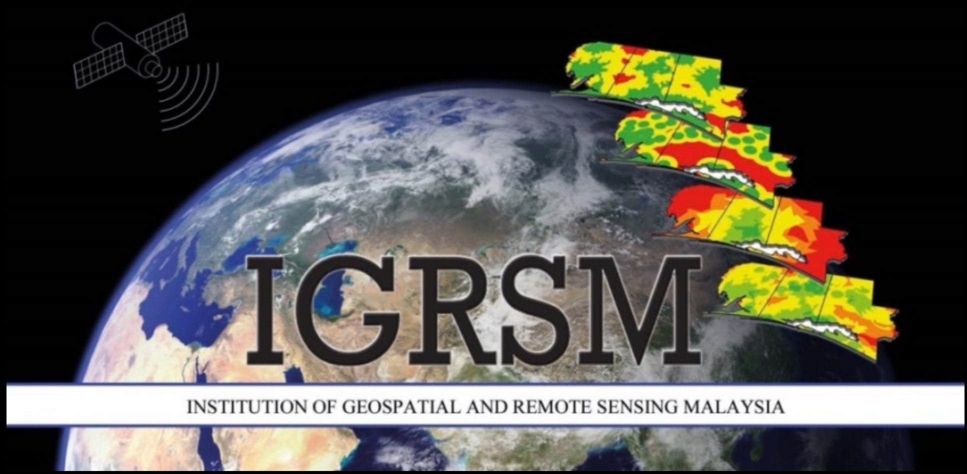

ANALYSIS OF AIR QUALITY AND NIGHTTIME LIGHT FOR INDIAN URBAN REGIONS

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ABSTRACT

Indian urban regions suffer from severe air pollution issues. A 2014 study by WHO highlighted that out of 20 cities globally with worst air quality, 13 lie in India. Although insufficient ground monitoring data and incomplete air pollution source characterization impedes putting policy measures to tackle this issue, remote sensing and GIS can overcome this hurdle to some extent. To find out how much of this hazard is due to economic growth, past researches have tried to make use of socio-economic growth indicators like GDP, population or urban area to establish its correlation with air quality in urban centers. Since nightlight has been found to correlate well with economic conditions at national and city level, an attempt has been made to analyze it with air quality levels to find regions with high contribution of anthropogenic emissions. Nighttime light activity was observed through DayNight Band (DNB) of VIIRS sensor while the air quality levels were obtained for ANG and AOD (using MODIS sensor) and SO_2 and NO_2 (using OMI sensor). We have classified Indian landmass into 4 air-quality and DNB classes: LowLight-HighPollution, HighLight-HighPollution, LowLight-LowPollution and HighLight-LowPollution for each air quality species using June 2014 data. It was found that around half of urban regions show high AOD and ANG values. On the other hand almost all urban regions exhibit high SO_2 and NO_2 values.

Keywords: *MODIS; OMI; VIIRS; economic activity classification.*

1. INTRODUCTION

Indian cities have some of the worst $PM_{2.5}$ and PM_{10} air pollution levels in the world, as was pointed out by World Health Organization (2014). In absence of sufficient temporal and spatial data from ground monitoring sensors, satellite imagery can be used to study pollution thanks to their long running data legacy. Socio-economic growth is one of the drivers of pollution which, among other drivers, varies with composition of economy (Dinda *et al.*, 2000) or social development indicators like literacy, population, etc. (Holian, 2014). In a previous study (Misra & Takeuchi, 2015) satellite data derived NO_2 and aerosol optical depth levels for 16 Indian cites were found to have high correlation with population (0.75) and population density (0.56), respectively. As a new approach and in absence of province level socio-economic data, studies are trying to analyze socio-economic growth by using nightlight data (Doll *et al.*, 2006). High correlations of nightlight with gross domestic product (GDP) (0.88) and motor-vehicle count (0.91) have been reported at national level by Katayama & Takeuchi (2014) on a global scale. For India, province or city level data of gross regional product (GRP) is not available barring few economic centers. Moreover, in developing countries it is often common for a lot of economic activities to be also centered around informal or unregulated industries whose estimates do not show up in national or state-level GDP values (Ghosh *et al.*, 2010). Such a study that incorporates informal economic sector too by using nighttime light as a proxy for economic activity to study air quality and human activity is being carried out for the first time for India and its urban centers.

The objective of this research is to analyze air quality species for Indian landmass and urban regions on the basis of economic activity. The specific aim is to classify air quality species: angstrom exponent (ANG), aerosol optical depth (AOD), SO_2 and NO_2 (collectively referred to as AQ hence) and nighttime light data into four classes based on histogram deduced threshold values. Thus, the percentage of pixels falling within each class shall reveal which AQ species is most related with economic activity induced human emissions.

2. DATA AND METHODOLOGY

2.1 Data Sources

2.1.1 Air Quality Data

To study ANG and AOD levels, daily 'MOD04L2' Level-2 data at 10km×10km resolution obtained from Moderate Resolution Imaging Spectroradiometer (MODIS) sensor onboard NASA's EOS Terra satellite for June 2014 was used. 'Deep_Blue_Aerosol_Optical_Depth_550_Land dataset was used for AOD images and 'Deep_Blue_Angstrom_Exponent_Land' dataset was used for ANG images. To study SO_2 and NO_2 column concentration levels for June 2014, 'OMSO2e' and 'OMNO2d' Level-3 Ozone Monitoring Instrument (OMI) datasets from NASA's EOS Aura were used respectively. This data has a spatial resolution of approximately 13km×24km. A mean monthly composite for all AQ species images was prepared using daily values.

2.1.2 Nighttime Light Data

To study nightlight radiance, monthly composite of day-night band (DNB) product (Baugh *et al.*, 2013) of Visible Infrared Imaging Radiometer Suite (VIIRS) dataset for June 2014 was used. It consists of light only from persistent sources. This data has not been filtered for forest fires, volcano activity, northern lights or any other activity that may generate light from natural sources. Its spatial resolution is approximately 0.75 km.

2.1.3 Land Cover Map

MODIS based global land cover map having a 0.5km resolution, developed by Broxton *et al.* (2014), based on 10 years (2001-2010) of Collection 5.1 'MCD12Q1' land cover type data was used.

2.2 Flowchart of This Study

Figure 1 lays down the flowchart of data selection, processing and analysis to obtain results.

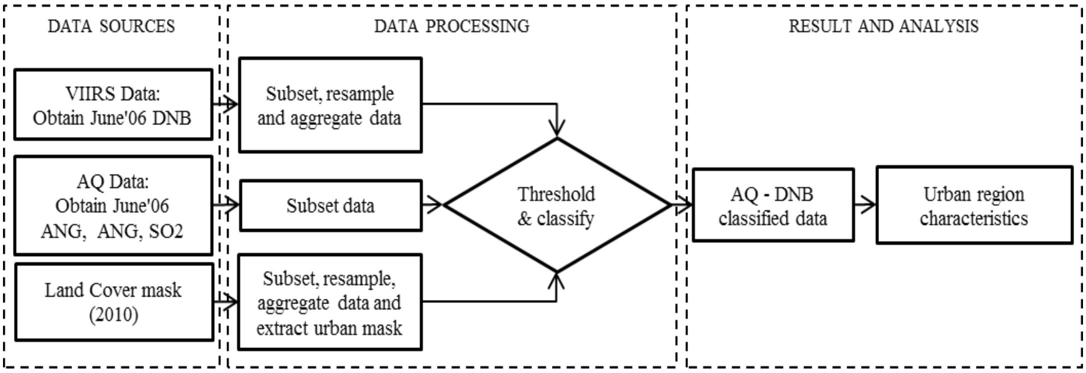

Figure 1: Flowchart of study outlining data sources, processing and analysis.

2.3 Classification by Economic Activity and Air Quality

Since economic activity levels can be judged fairly well from the nightlight observed from space, first the Indian administrative region was subset from all the data sources using the shapefiles developed by Hijmans (2009). Since any forest fires were not reported during June 2014, DNB image was used without any corrections. Further as DNB monthly composites have higher resolution, it was downscaled to the coarser resolution of MODIS and OMI by mean aggregation to enable a pixel level comparison. These downscaled DNB images at the resolution of MODIS and OMI are henceforth referred to as DNB_{MODIS} and DNB_{OMI} respectively. Downscaling factor used were 20 and 60 respectively.

As the objective is to classify regions on the basis of socio-economic activity data (nightlight values in this case) and AQ data, we needed to identify a binary threshold to bin the data into low and high values. For this binned frequency histograms for each AQ parameter and DNB values were plotted. Histograms were then thresholded either at valley or peak of the trend plot. Then using the threshold values for each AQ parameter and nightlight values (DNB), the region was classified as: a) LowLight-HighPollution (LLHP), b) HighLight-HighPollution (HLHP), c) LowLight-LowPollution (LLLP) and d) HighLight-LowPollution (HLLP). The classification scheme is show in Figure 2 for clarity.

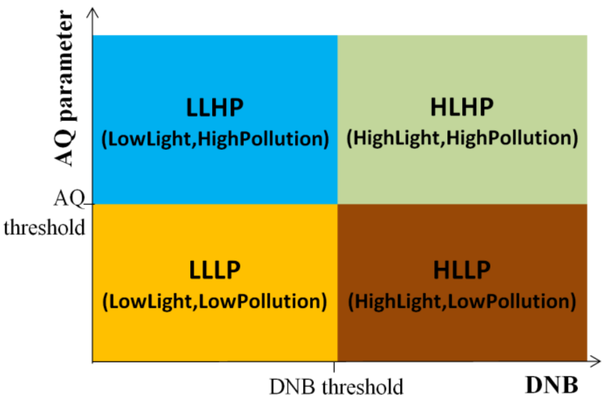

Figure 2: Classification scheme followed based on high and low AQ parameter values and DNB values. The 4 classes: LLHP, HLHP, LLLP, HLLP are colour coded as per their respective quadrant colour.

The HL regions signify locations of non-agricultural economic activity. They may not necessary be urban regions but may also include factories or industrial areas often situated outside urban limits. Similarly LL regions include mountainous, forest, deserts and other regions with no or very less human activities. Since all villages do not share the same economic development characteristics they may fall in a LL or a HL region.

In the next part of processing 'urban and built-up' class map was prepared from the Land cover map data. Since the class mask was at higher resolution than MODIS and OMI, it was downscaled using a kernel block of size 20 and 60 respectively. Urban regions in various Indian towns and small cities are often not as large as a MODIS or OMI pixel. To preserve those urban regions in the downgraded urban cover mask, if at least ¼ pixels in the kernel block belonged to urban class, the whole block was marked as urban. Using this urban mask, percentage of urban region was classified to find about their characteristics.

3. RESULTS AND DISCUSSION

After subsetting data for Indian boundary region, DNB image was downscaled to resolution of MODIS and OMI respectively. In order to obtain classification thresholds, the following histograms were generated as shown in Figure 3.

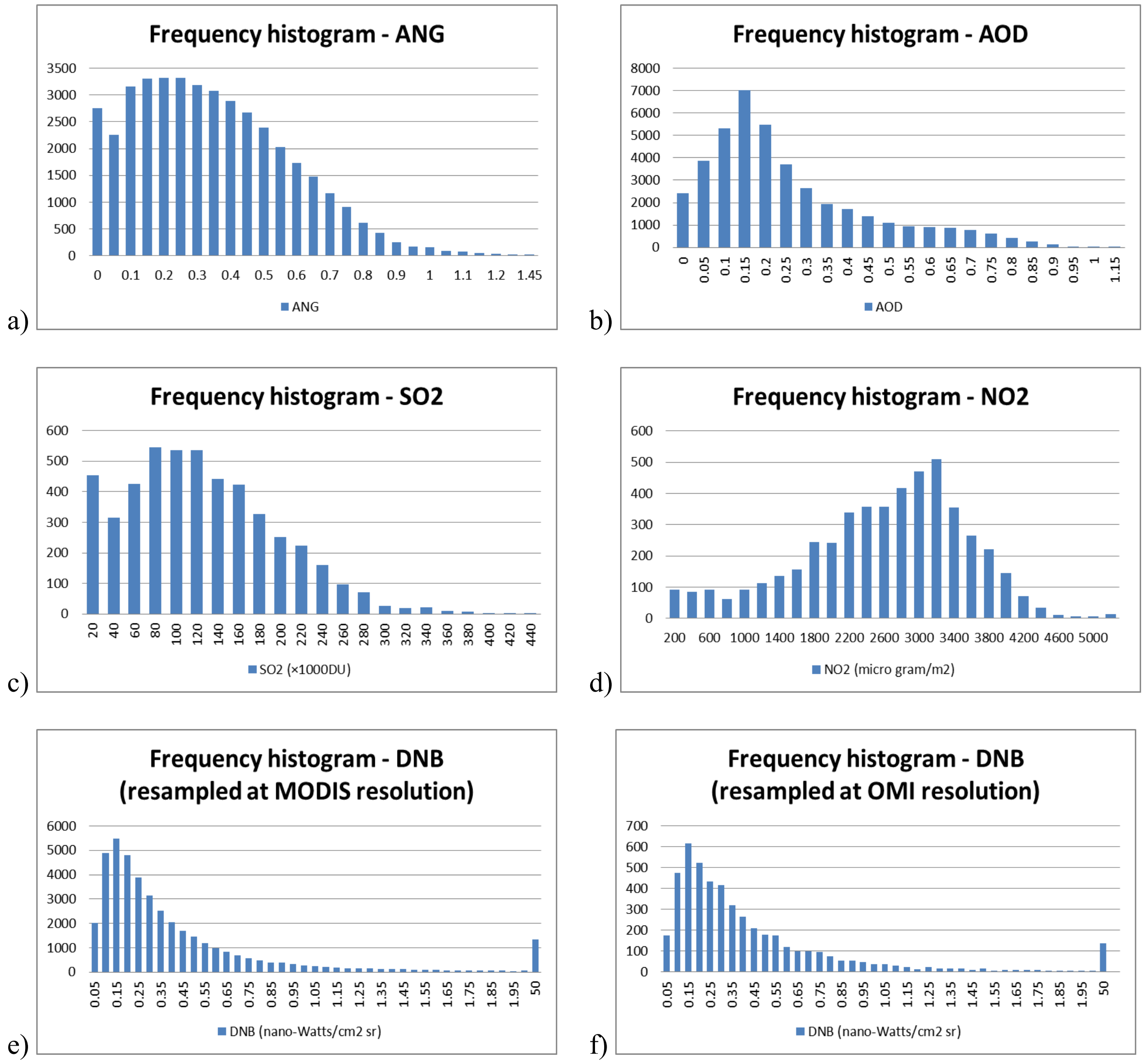

Figure 3: Threshold values for all the image datasets. a) ANG threshold at 0.2, b) AOD threshold at 0.25, c) SO_2 threshold at 100E3 DU, d) NO_2 threshold at 2000 microgram/m^2, e) DNB_{MODIS} threshold at 0.3 nanoWatt/cm^{2}sr, f) DNB_{OMI} threshold at 0.3 nanoWatt/cm^{2}sr.

The histogram plot were not found to be bimodal, which otherwise would have led to easier identification of thresholds. Instead others inflection point values of the plot were checked for their suitability as threshold values. For ANG, SO_2 and NO_2 the first valley comes quite early in the plot (at 0.05, 40(×1000 DU) and 800 microgram/m^2 respectively). However considering they are physically too low to serve as threshold, the next inflection points in the histogram plot were chosen as thresholds. DNB_{MODIS} showed sharper trends in lower mid-ranges of 0.15 to 0.75 nanoWatt/cm^{2}sr compared to DNB_{OMI}. This was expected since DNB_{OMI} was obtained by degrading the original DNB image to a greater extent than DNB_{MODIS}. Threshold of 0.3 nanoWatt/cm^{2}sr was chosen because a lower inflection value from the plot could not distinguish the human inhabitance of regions based on light. For determining AOD threshold, inflection values were adjudged to be either too high or too low compared to their physical suitability. So, we tried to find an approximate AOD equivalent of particulate matter (PM2.5 and PM10) based WHO 24-hour mean air-quality guidelines (25µg/m^3 and 50µg/m^3 respectively) (World Health Organization, 2006). By using AOD and PM regression relationships developed for the cities of New Delhi (Kumar *et al.*, 2007) and Agra (Chitranshi *et al.*, 2015) approximate corresponding AOD values were obtained. Based on those values, 0.25 (no dimension) was adjudged as a suitable AOD threshold. Thus, thresholds were chosen as 0.2 for ANG, 0.25 for AOD, 100(×1000 DU) SO_2, 2000 microgram/m^2 for NO_2 and 0.3 nanoWatt/cm^{2}sr for both DNB_{MODIS} and DNB_{OMI}. Most of the frequency histograms in Figure 3 follow a left skewed shaped curve, implying that the bulk of pixels have low values. However for NO_2, the bell shaped curve is right skewed. Thus it can be inferred that higher NO_2 values are more common than lower values. Using the combination of threshold values of AQ parameters and DNB (as inferred from the plots in Figure 3) and following the classification scheme mentioned earlier, classified maps for India were developed. These maps are shown in Figure 4.

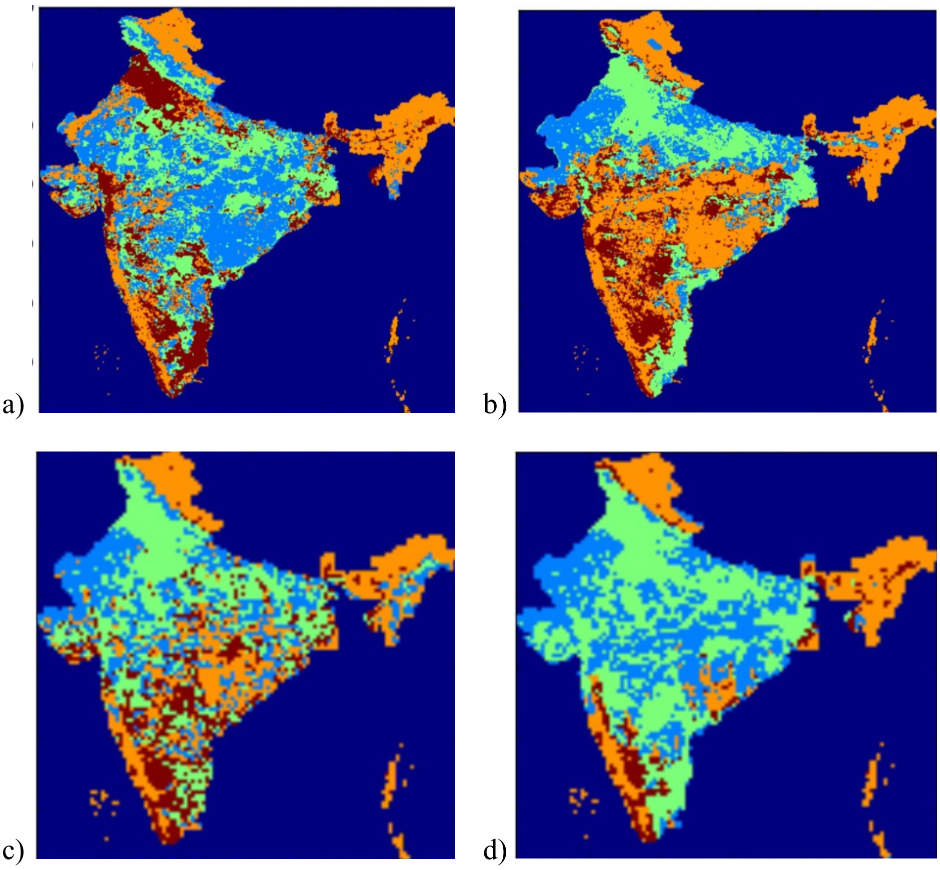

Figure 4: AQ parameter (a-ANG, b-AOD, c- SO_2, d- NO_2) and nightlight (DNB) classified map of India. The legend used is same as Figure 2:

From classification maps in Figure 4, it was found that most of LLHP and HLHP regions lie in mainland northern regions. Some cities in the eastern regions also show LLHP and HLHP and stand out isolated from their surroundings. The eastern coast of southern India shows dominance of HLHP region while the western region shows existence of LLLP regions. A region in northern western edge of India shows HLHP for AOD, SO_2 and NO_2 yet shows HLLP for ANG values.

Since low ANG values point to the existence of mineral dust, it can be deduced that those regions are highly industrialized and face severe pollution not only from man-made sources (as can be seen from NO_2 and SO_2 maps) but also a high amount of mineral dust. The small islands of HLHP within the HLLP belt in the north Indian part of ANG-DNB classification map are actually cities of Ludhiana, Amritsar and New Delhi. Amongst cities, they tend to have some of the highest ANG levels in the country (Misra & Takeuchi, 2015).

To explore which classes do the urban regions belong to, these classification map were overlaid with the land cover map. The comparison of urban and non-urban pixel values is presented in Figure 5.

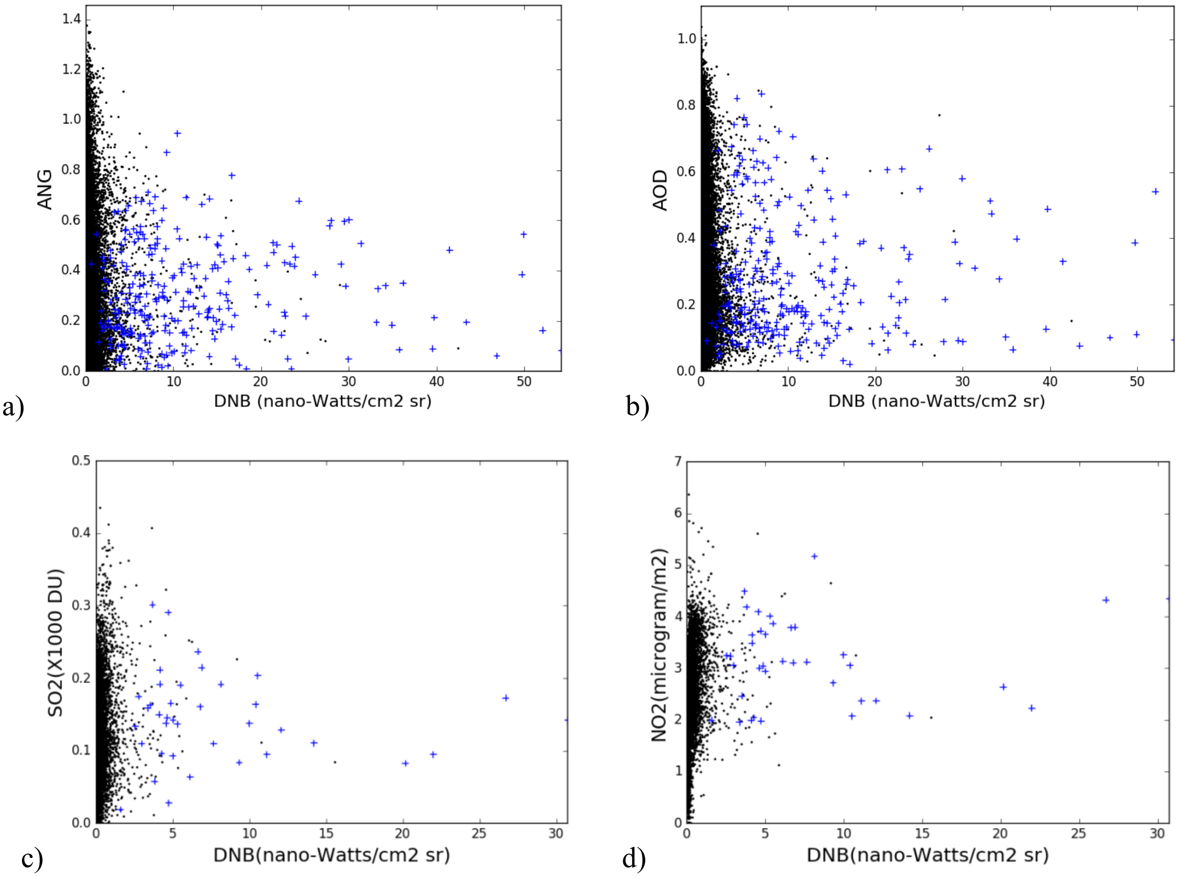

Figure 5: Comparison of urban and non-urban pixels on the basis of AQ parameter (a-ANG, b-AOD, c-SO_2, d-NO_2) and nightlight (DNB). Urban pixels are represented by + while non-urban pixels are represented by ●.

The urban pixels can easily be spotted due to their high DNB values. However considering the threshold of DNB, which is set at 0.3, there are considerable locations which despite not being urban or built-up still have high DNB and AQ values. They are likely to be the suburban areas around the cities. In our analysis, urban pixels represented only 0.7% of all pixels which is considerably less than the reported urban area (2.35% of Indian land mass) for the year 2008 by the Department of Land Resources (2013). Thus there is under-representation of urban regions in the land cover map. Also identity of original urban mask pixels has diminished due to resampling and downgrading.

In Table 1, classification result of urban regions is presented. As discussed earlier only high nightlight (HL) region pixels were identified as urban.

Table 1: Classification percentages of different classes for urban regions.

Urban AQ & DNB map	LLHP	HLHP	LLLP	HLLP
ANG & DNB	0.00%	54.51%	0.00%	45.49%
AOD & DNB	0.00%	54.51%	0.00%	45.49%
SO_2 & DNB	0.00%	73.68%	0.00%	26.32%
NO_2& DNB	0.00%	89.47%	0.00%	10.53%

Incidentally the percentage of pixels identified as HLHP and HLLP is exactly same for ANG-DNB and AOD-DNB maps. It remains to be checked if indeed they are also the same pixels. The problem of SO_2 is comparatively much higher in HL regions while high NO_2 pollution seems to exist almost only in HL regions. Thus, almost half of the urban regions have relatively high aerosol levels. In contrast a much greater number of urban regions have higher values of SO_2 and NO_2. This implies that SO_2 and NO_2 emission sources (e.g. vehicle emissions, biomass burning) are almost present in all urban regions. Whereas about half of the urban regions have greater (or stronger) number of aerosol sources that are not present in other urban regions. This implies the almost all urban areas are similar in respect to SO_2 and NO_2 emissions sources but about one half of the urban regions are different from the other half in terms of aerosol sources. This is an important result to check the source of aerosol in urban regions. Also it can also be used to predict disease outbreaks likely to be born out different polluting species.

As a next step, a more recent land cover map should be used to generate urban cover mask to analyze this in detail. If sufficient urban pixels can be detected then thresholding could be done on the urban pixels to assess classification of urban region. Also combining the result with a population density raster can inform the number of people at health-risk due to anthropogenic pollution.

To study a long term trend, workflow of this analysis can be adapted to the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) datasets. It has a long-running legacy and can be used with data MODIS and OMI data which is available since 2001. As a final step if this analysis is performed for multiple periods using DMSP-OLS and VIIRS-DNB datasets, how cities transition from one AQ-DNB class to another can be studied.

4. CONCLUSION

In this study, Indian landmass was classified according into regions with 4 different levels of air quality and economic activity by thresholding their histograms into 'high' and 'low'. By using urban land cover mask this process was also applied to urban areas where it was found all urban area lie in high light regions. NO_2 levels was found to be significantly high for about 90% urban area while SO_2 levels was found to be high for about 74% urban area. ANG and AOD classification exhibited a similar behavior with same percentage of pixels being identified as high (about 55%). Using the same methodology, we wish to process DMSP-OLS data and study how classification behavior of urban regions has changed in the past 15 years. This can help locate regions where air quality has changed under influence of its economic activities

Nomenclature of Abbreviations Used

ANG	Angstorm Exponent; used to study the size of particulate matter in air. Larger values indicate smaller size of particulate matter particles
AOD	Aerosol Optical Density; used to study the density of particulate matter in environment
AQ	Air Quality species considered in this study, namely:
DMSP-OLS	Defense Meteorological Satellite Program's Operational Linescan System
DNB	Day Night Band
DNB_{MODIS}	DNB image resampled to MODIS resolution
DNB_{OMI}	DNB image resampled to OMI resolution
DU	Dobson Unit - measurement of the columnar density of a trace gas in the Earth's atmosphere
EOS	Earth Observation Satellite
GDP	Gross Domestic Product
GRP	Gross Regional Product
HLHP	HighLight-HighPollution class
HLLP	HighLight-LowPollution class
LLHP	LowLight-HighPollution class

LLLP	LowLight-LowPollution class
MODIS	Moderate Resolution Imaging Spectroradiometer satellite sensor
NO_2	Nitrogen Dioxide
OMI	Ozone Monitoring Instrument satellite sensor
$PM_{2.5}$, PM_{10}	Particulate matter with mean aerodynamic diameter less than 2.5µm and 10µm respectively
SO_2	Sulphur Dioxide
VIIRS	Visible Infrared Imaging Radiometer Suite
WHO	World Health Organization

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