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Changes in nighttime lights during COVID-19 lockdown over Delhi, India

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4.1 Introduction

Conventional studies analyzing the electricity sector considers the consumption profile with respect to direct factors only. These factors affect the rate and cost of production of electricity and its consumption based on commercial, domestic, and essential demands. During COVID-19 crisis, these analyses fail to be relevant because impact of COVID lockdown on commercial EPC is not considered. Also, the factors like reduction in societal activities & increase in stay-at-home population during COVID lockdown were not taken into account.

There exists multidomain correlation between various factors like stay-at-home population, lockdown of commercial and industrial sectors, COVID-19 cases and deaths reported, mobility reported in various sectors, etc. When these factors are considered cumulatively, they can give insights into the impact on electricity sector during the lockdown. A similar approach has been followed for analyzing the short-run impact of COVID-19 on the U.S. electricity sector (Ruan et al., 2020). This is a new approach in the Indian scenario and very few attempts analyzing the impact of COVID-19 on the electricity sector of India has been made following this cross-domain approach.

Nighttime lights (NTL) has been used in several studies as a proxy measure for electricity consumption or to predict energy distribution in an area (Falchetta et al., 2019, 2020; Falchetta & Noussan, 2019; Román, Stokes, et al., 2019; Ruan et al., 2020). The spread of infectious diseases and the factors responsible in triggering the spread have also been explored in some studies using NTL imagery as a measure to monitor the human mobility and its effects on the morbidity rates (Donalisio et al., 2020; Lai et al., 2019; Small et al., 2020; Tizzoni et al., 2014; Zhao et al., 2019). The referred studies have used NTL, individually, as a proxy measure for electricity consumption and human mobility for assessing spread of infectious diseases. The use of multidimensional correlation, in our study, for analyzing the impact of COVID-19 on electricity sector cumulatively using NTL, is a new approach, especially in the Indian scenario.

Román et al. (2018) introduced NASA's Black Marble NTL product suite (VNP46A1) which was developed to realize the full potential of the VIIRS DNB time series data. At 500 m spatial resolution and a temporal resolution of 1 day, the dataset provides global coverage of corrected NTL within 3–4 hours of acquisition. The daily NTL provided by VNP46A1 is enhanced and corrected for various atmospheric, terrain, vegetation, snow, lunar, and stray light variations and other intrinsic surface optical properties (Román et al., 2019). The corrections made for nonlinear changes in phase and libration using lunar irradiance model, for atmospheric and bidirectional reflectance distribution function (BRDF) effects, for seasonal vegetation variations in NTL and for temporal data gaps, makes it a current state-of-the-art for NTL applications.

This study aims to monitor the changes in the NTL using NASA's Black Marble Product Suite (VNP46A1) during COVID-19 lockdown over Delhi, India. It focusses on using NTL as a proxy measure to study electricity consumption and how it has been impacted during lockdown. Along with NTL, multidomain datasets like number of cases confirmed and deceased, reported due to COVID-19, mobility data in various sectors and daily electric power

consumption (EPC) dataset have been considered to study the impact on the electricity sector due to other factors prevailing amid COVID-19 crisis.

4.2 Study area and data used

Delhi, containing New Delhi, the capital of India, has been considered as the study area. It is located at the centroid coordinates of 28°38′47.4″ N, 77°6′32.04″ E. The location map of study area is shown in Fig. 4.1. Delhi has been identified as one of the major hot spots of COVID-19 in India with over 174,748 confirmed cases and 4,444 deaths as reported on August 31, 2020 (COVID19 Statewise Status, 2020).

The following datasets have been used in our study:

1. NTL data—The NASA's Black Marble Product Suite (VNP46A1) for the image tile H25V06 containing Delhi is taken for the months of March, April, and May of 2019 and 2020 available on a daily basis at 500m spatial resolution (NASA LAADS DAAC VNP46A1-5000, 2019). The processed data is available within 3–5 hours of acquisition in HDF5 format from which the raster layers containing radiance at sensor and quality flags information has been extracted and saved as GeoTiff for further processing and analysis.

2. Mobility data—The community mobility dataset created by using location information provided by Google (Google COVID-19 Community Mobility Reports, 2020), highlights the percentage change from a baseline in mobility at places like grocery stores, transit stations, workplaces, parks and residential areas. The baseline is created considering the median value, for the corresponding day-of-week, during the five-week period January 3 – February 6, 2020. The data is present in CSV format, on a daily basis at state level for different countries out of which Delhi, India data is used for the period of March, April, and May, 2020.

3. COVID-19 data—The API made available by covid19india.org (COVID-19 India API, 2020), is used to extract state-wise daily data of the number of COVID-19 confirmed and deceased cases (per day) for Delhi and saved
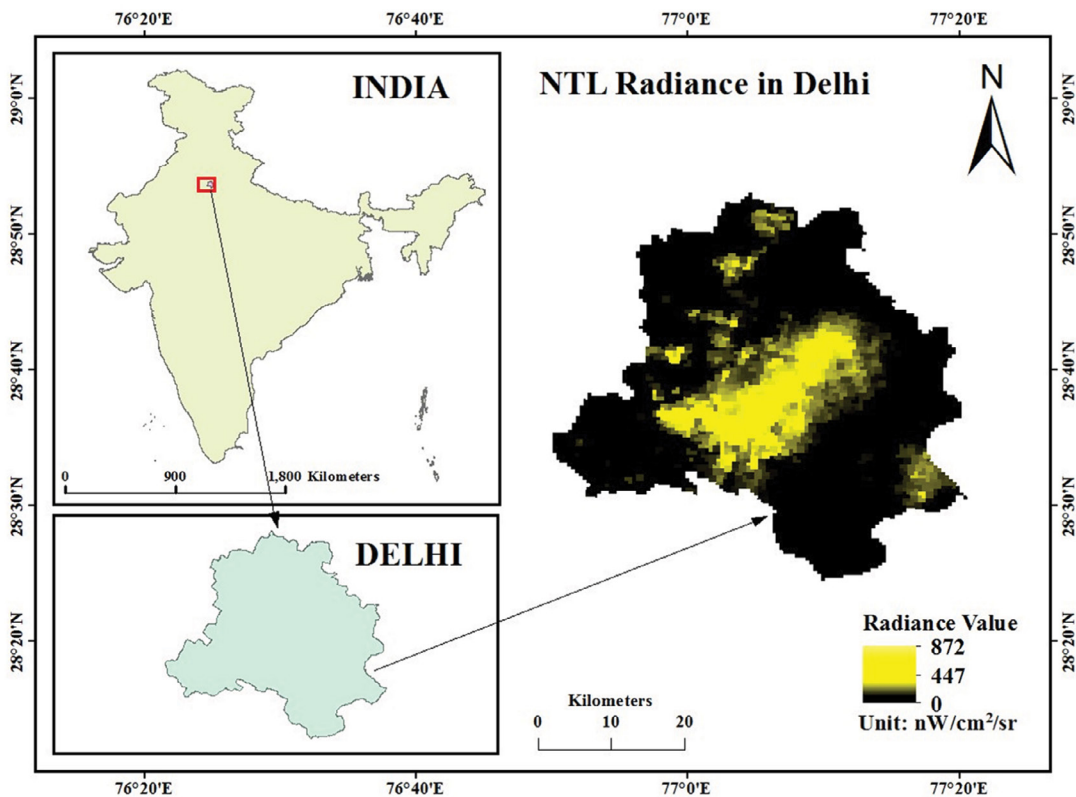

FIG. 4.1   Location map of study area.

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in CSV format for further processing. The data is available from Mar 14, 2020 onwards till the time 7 cases for Delhi were reported with no deaths.

4. Electricity Consumption data—The data is collected from the Power System Operation Corporation Limited (POSOCO), which is a Government of India (GoI) owned enterprise under the Ministry of Power (Daily Reports - National Load Dispatch Centre, POSOCO, 2020). POSOCO ensures the integrated and reliable operation of India's grid. The daily reports of electricity consumption are made available with a delay of one day in pdf formats. While the total electricity consumption in these documents is not broken down between different uses like residential, commercial, etc., but it provides the daily EPC data in Mega Watts (MW) at the state-level. The daily pdf documents were downloaded and exported as CSV using the Python library Tabula.

4.3 Methodology

The flowchart (see Fig. 4.2) represents the stepwise methodology adopted in our study. The NTL data from NASA's Black Marble product is taken as input. The radiance at sensor and Quality Flag (QF) layers (Román et al., 2019) are extracted as GeoTiff files. Next, the steps of clipping the rasters to study area and scaling is done and unambiguous

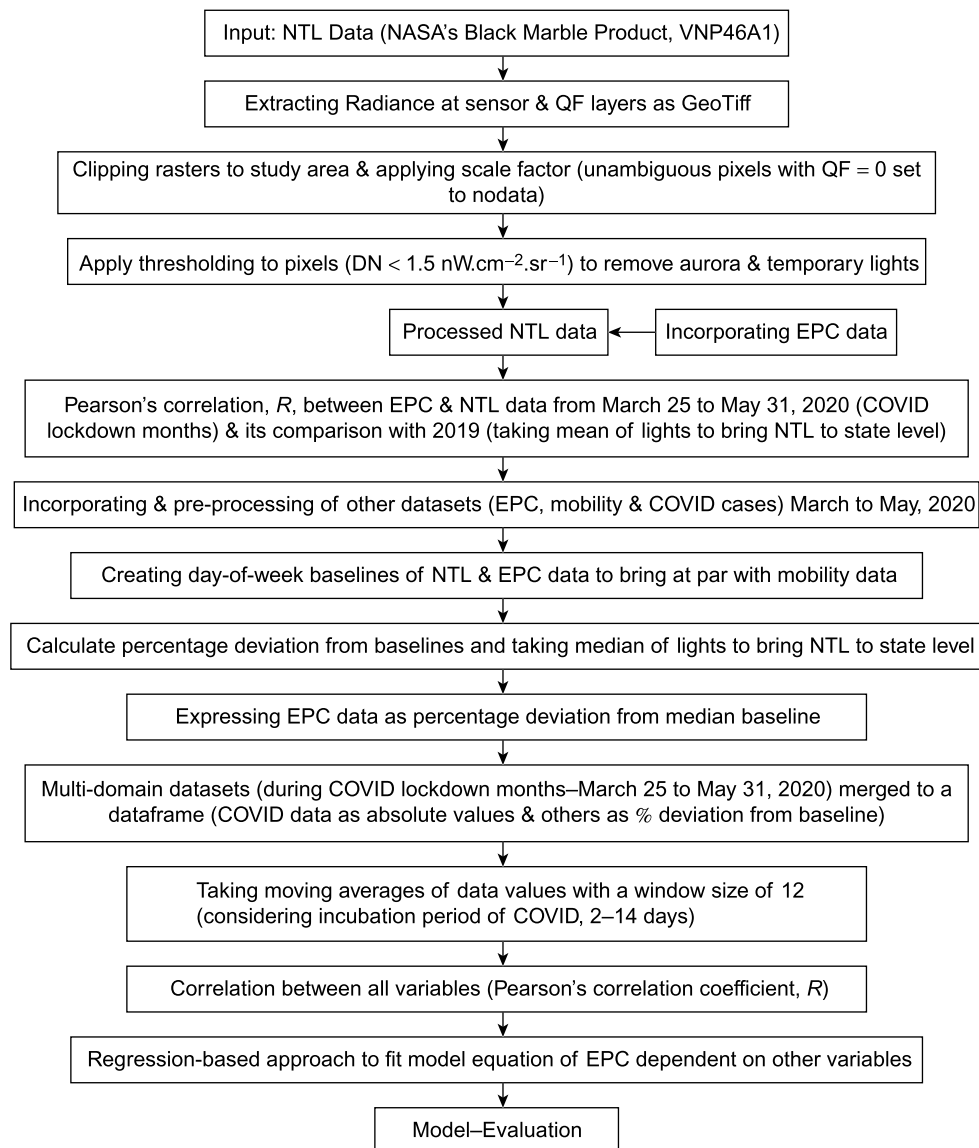FIG. 4.2   Flowchart depicting the methodology adopted in this study.

pixels are set to NODATA. A threshold of 1.5 $nW.cm^{-2}.sr^{-1}$ is applied and pixels below this threshold are set to NODATA to remove aurora and temporary lights. The processed NTL data is thus obtained.

The EPC data is incorporated with the NTL data and its pre-processing is done. In the next step, the correlation between EPC and NTL for COVID-19 lockdown months from March 25 to May 31, 2020 is obtained and compared with the correlation between these two for the same time period for the previous year, i.e. March 25 to May 31, 204. For this mean of lights is taken to bring NTL to state level, ignoring NODATA values. Taking mean of lights is one of the popular methods for aggregation of NTL. Other previously used methods are sum of lights (SOL) (Elvidge, et al., 2009), median of lights, etc.

The next step is the incorporation of other datasets which are mobility and COVID cases. The creation of day-of-week baselines to bring NTL and EPC data at par with the mobility data is done. The baseline is created considering the median value, for the corresponding day-of-week (Sunday, Monday, Tuesday, Wednesday, Thursday, Friday, and Saturday), during the five-week period January 3–February 6, 2020. Using this, seven NTL images for each day-of-week for five consecutive weeks are stacked together. The percentage deviation from baseline is calculated for each NTL image from March 1 to May 31, 2020. The median of lights is taken to bring NTL to state level. Similarly, for EPC data, present as daily lumped quantity, the respective day-of-week baseline values are calculated and then expressed as percentage deviation from baseline. The COVID cases are taken as absolute values here.

Thus, the multidomain dataset during COVID-19 lockdown months is obtained as a single merged dataframe. A dataframe is a 2-D data structure where data is aligned in row and column format. Here, a dataframe is formed by merging the multidomain datasets using Pandas package in Python. The moving average with a window size of 12 days is taken for these datasets. This value is taken because the incubation period of COVID-19 is 2–14 days which means that symptoms of COVID-19 may appear within 12 days of exposure to the virus (Centres for Disease Control and Prevention, 2020). The moving averages help to clear out the noise in data from day-to-day fluctuations and smoothens it. This gives a clear view of trends present in the data and makes the analysis easier.

Next, the correlation between these multidomain datasets is obtained and studied. A symbolical regression-based approach for obtaining a model equation of EPC depending on the said variables is followed (Schmidt & Lipson, 2009). The insights from the model equation for predicting future trends in EPC are discussed.

4.4 Results and discussion

This section is subdivided into four sub-sections including (i) exploration of individual datasets, (ii) results of comparison of correlation between NTL and EPC with previous year, (iii) results of correlation of the multi-domain datasets during COVID-19 lockdown, and (iv) symbolical regression-based approach for predicting EPC and discussion on the insights.

4.4.1 Exploration of individual dataset

4.4.1.1 COVID-19 dataset

The COVID-19 dataset containing the number of cases confirmed and deceased per day during COVID-19 lockdown period from March to May, 2020 have been displayed in Fig. 4.3.

The dataset contains the reported number of confirmed and deceased COVID cases per day. The data is available from March 14, 2020 onwards until then seven confirmed COVID cases with one death were reported. A sudden increase in the confirmed cases after March 25, 2020, when the lockdown was imposed as the symptoms of COVID-19 are seen after 2–14 days of exposure to virus. The deaths reported are very less as compared to the confirmed cases. The irregularity in the data could also be due to nonreporting, underreporting, or misreporting of cases, overwhelmed public health infrastructure, and intermediate strictness measures taken by the state government.

4.4.1.2 Mobility dataset

The dataset shows mobility as percentage deviation from the baseline in the six sectors namely—Retail and Recreation, Grocery and Pharmacy, Parks, Transit Stations, Workplaces, and Residential (see Fig. 4.4). The first dip in the dataset on March 10, 2020 shows decreased mobility in all other sectors whereas an increased mobility in residential areas. This might be due to National holiday for the festival of *Holi* in India. The next dip is seen on March 25, 2020 when the lockdown was imposed in the whole nation. The mobility in commercial sectors has shown a decrease
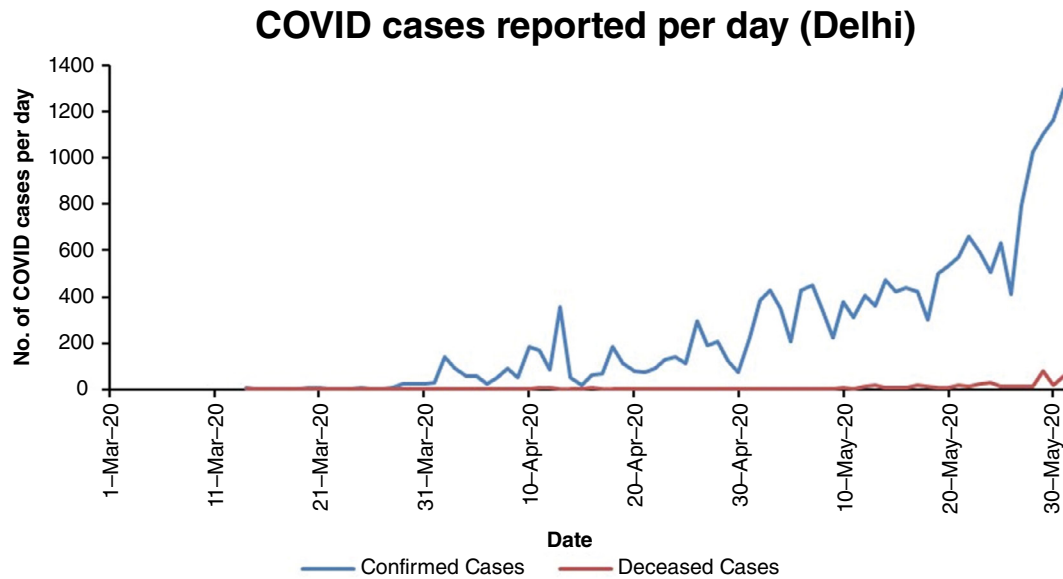
COVID cases reported per day (Delhi)

FIG. 4.3 COVID cases, confirmed and deceased, reported per day from March to May, 2020 (Delhi).

from baseline whereas mobility in residential areas has shown an increase, which is due to increase in stay at home population during lockdown.

Our analysis is mainly focused from March 25, 2020 onwards to study the correlation of mobility with other variables considered. The data shows gradual increase in mobility under the category "Transit Stations"; this confirms the news articles on post lockdown mass movements of low- and middle-income workers and laborers back to their hometowns. Several states allowed markets to be opened on certain days of the week, which is seen in the spikes in the "Retail and Recreation" category. A marked dip is seen around April 15, 2020 in the "Parks" category, which clearly represents the extension of lockdown to the next phase by the central government with more stringent restrictions on going out to nearby common places like parks, etc. Two marked jumps can be seen in "Grocery and Pharmacy" sector after April 30, 2020 and next around May 20, 2020. These might be due to the increase in mobility observed after giving conditional relaxations to essential places like medical and grocery stores in the regions where the spread was contained. The jumps and dips in "Workplaces" and "Residential" categories respectively show a complimentary trend which corresponds to the fact that attendance was made compulsory once a week in various government offices and other workplaces during the lockdown months.

4.4.1.3 NTL Dataset

The NTL data as expressed as percent deviation from baseline has been shown in Fig. 4.5. The moving averages with a window size of 12 days is taken and median of lights is considered to bring NTL to state level. The night
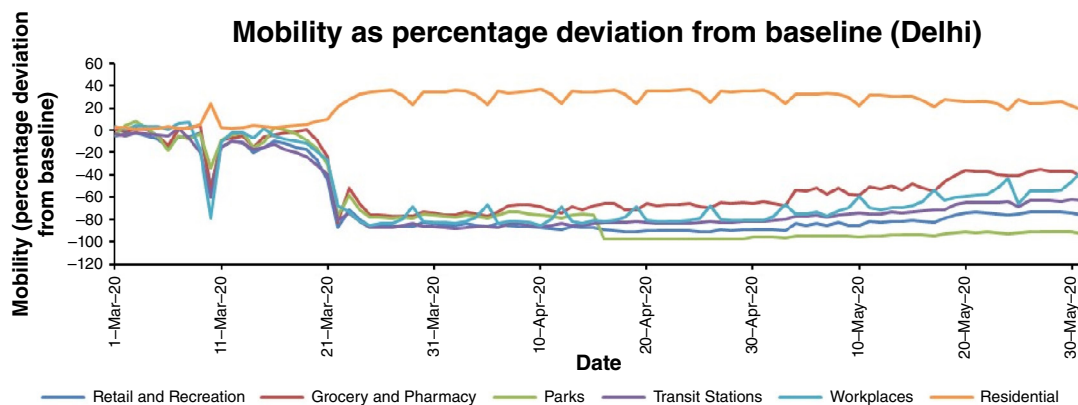

FIG. 4.4 **Mobility as percentage deviation from baseline (Delhi).** The various sectors involved are: mobility at - retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential.
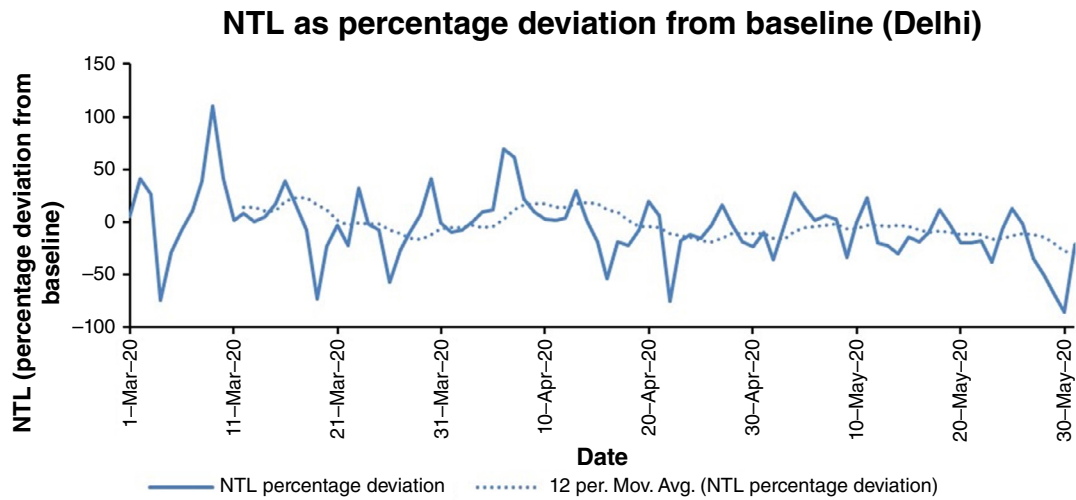
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NTL as percentage deviation from baseline (Delhi)

FIG. 4.5   **NTL expressed as percentage deviation from baseline (Delhi).** The moving averages with a window size of 12 days is taken and median of lights is considered to bring NTL to state level.

before the festival of *Holi*, there is a widely followed religious practice of lighting bonfires. This can be seen in the peak on March 9, 2020. The deviations in NTL shows dips which appear to be inconsistent with any of the mobility categories. However, similar to most mobility categories, a negative trend is also observed in the NTL dataset. This can be clearly seen in the moving averaged data. A similarity in the NTL trend can be seen with the mobility in residential areas after lockdown was imposed.

Fig. 4.6 shows how percentage deviation in NTL from baseline has varied with respect to the day-of-week during COVID-19 lockdown months. It shows that there is more positive deviation on Monday and less negative deviation on Friday. This implies that NTL captured during lockdown months shows greater negative deviation on weekends especially Friday because of restrictions and shut down of commercial places.

4.4.1.4 EPC Dataset

The EPC (in MW) data from POSOCO during COVID-19 lockdown period has been plotted with respect to date as shown in Fig. 4.7. The dataset provides the daily EPC in Mega Watts (MW) at the state-level. A dataset giving breakup of total EPC into different sectors like residential, commercial etc. is unavailable. The available dataset has been used in the comparison with absolute NTL values. The EPC data expressed as percent deviation from baseline

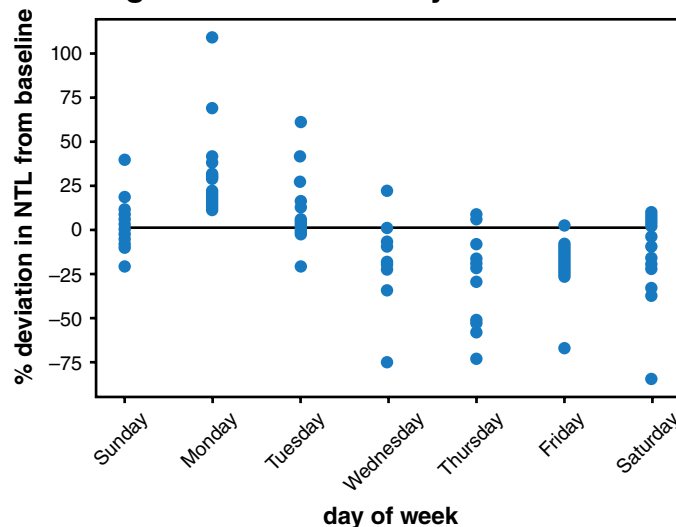## NTL percentage deviation with day–of–week during lockdown

FIG. 4.6   **NTL percentage deviation from baseline w.r.t day-of-week during lockdown.**

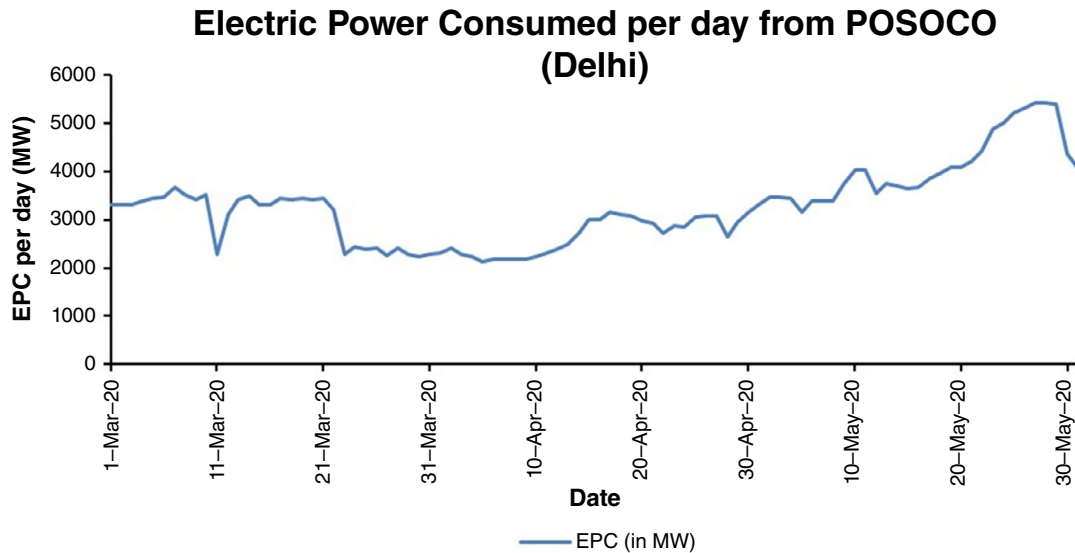**Electric Power Consumed per day from POSOCO (Delhi)**

FIG. 4.7   **EPC per day (in Delhi) during lockdown months.**

(January 3–February 6, 2020) has also been shown in Fig. 4.8, which has been used in the correlation with other variables.

Due to increased EPC in the winter season (January–February; used to generate the baseline), the reduced EPC in March–May (summer season) appear as negative, as shown in the negative values of percentage deviation of EPC from baseline. The EPC deviation data shows consistency with the mobility datasets as the first dip is shown on March 10, 2020. The further trends after lockdown was imposed, i.e. March 25, 2020 are also similar. The EPC although does not show much similarity with the trends in NTL data. To get more insights on the correlation between each variable, Pearson's correlation coefficient, R is calculated pairwise.

4.4.2 Comparison of correlation between NTL and EPC with previous year

The correlation between average radiance values of NTL and the EPC data (in MW) has been studied during COVID-19 lockdown period and has been compared with that of the same months, i.e. March 25 to May 31 for 2019. This is done to study the effect of COVID-19 on the correlation of the two variables compared to previous year. This study is done with absolute values of NTL and EPC (the percentage deviation or moving average values have not
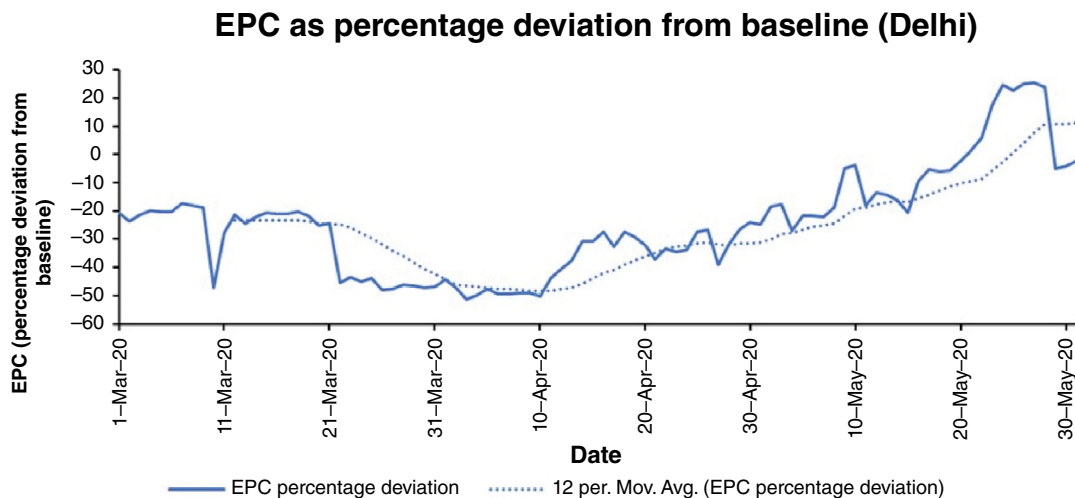
EPC as percentage deviation from baseline (Delhi)

FIG. 4.8   **EPC expressed as percent deviation from baseline (Delhi).** The moving averages with a window size of 12 days is taken for EPC data.
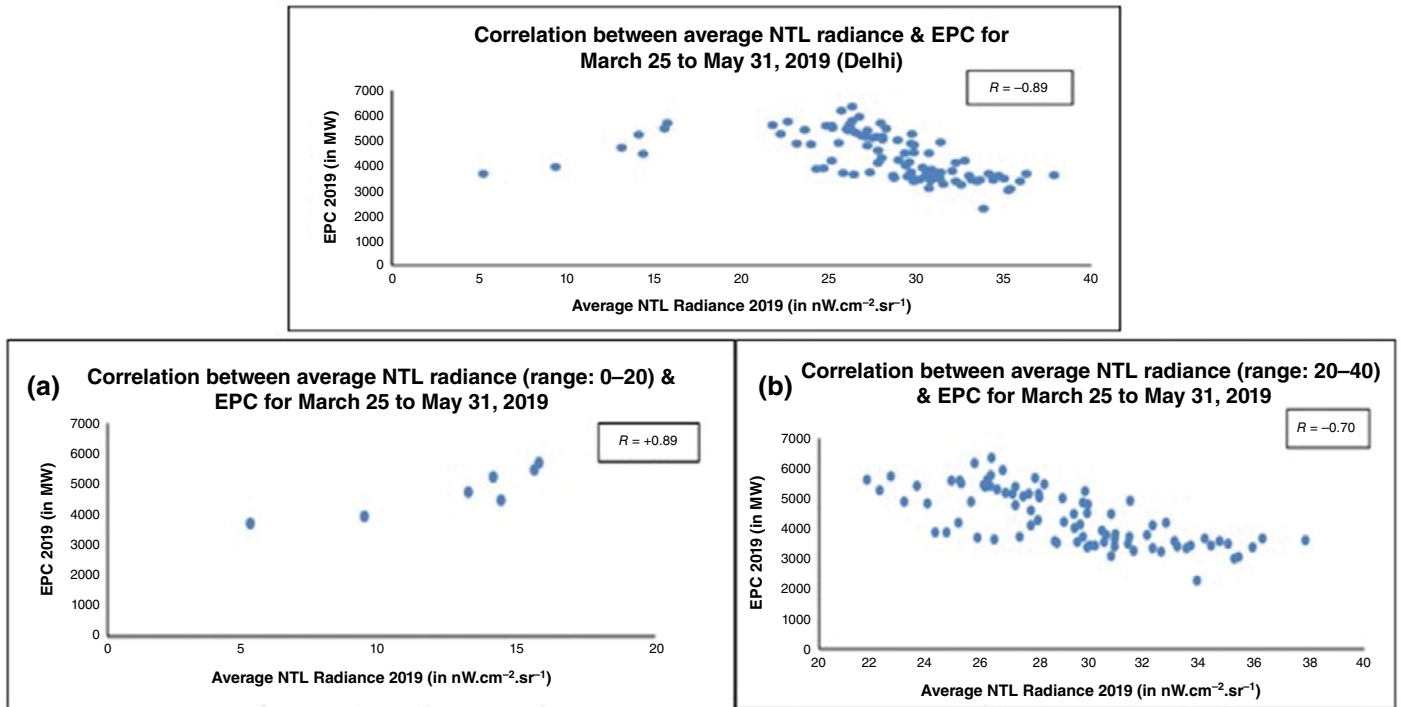
FIG. 4.9   Correlation of NTL and EPC for 2019 with radiance values categorized as (a) full range 0-40 (b) range 0-20 (Residential) (c) 20-40 (Transit stations, parks, workplaces, and other commercial sectors).

been considered here). The Fig. 4.9 shows high negative correlation between average NTL radiance and EPC data for 2019 for Delhibut if we split the NTL data and consider the range of NTL radiance values from (a) 0–20 nW.cm^{-2}.sr^{-1} and (b) 20–40 nW.cm^{-2}.sr^{-1}, it clearly shows a separate relationship between NTL and EPC considering the NTL radiance threshold value of 20 nW.cm^{-2}.sr^{-1}. This threshold matches with the threshold value considered by Liu et al., 2020. He has mentioned three different ranges of NTL radiance as 5–20, 20–40, and greater than 40 (nW.cm^{-2}.sr^{-1}) which are appropriate radiance ranges for residential areas, transportation and public facilities and commercial centres, respectively. In Fig. 4.9a, there seems to be high positive correlation for NTL < 20 implying that low lit areas, particularly residential areas, have positive correlation with EPC for the year 2019, whereas, highly lit areas (transit stations, parks, workplaces and other commercial sectors like retail and recreation, and grocery and pharmacy) have negative correlation with EPC (Fig. 4.9b). The high magnitude of Pearson's coefficient shows high correlation of EPC with highly lit areas, although a negative sign could be because the EPC data taken is a cumulative figure. EPC data with breakup of total consumption into different categories (as mentioned in Section 4.2) can give better insights on the correlation.

But for the year 2020, during COVID-19 lockdown months, the correlation between NTL and EPC in both ranges for NTL < 20 and NTL > 20 shows a weak negative correlation as shown in Fig. 4.10. The decrease in the magnitude of correlation in 2020 can be attributed to the effect of COVID-19 lockdown. Because of the nationwide lockdown, most of the commercial sectors were shut down which has highly affected the total EPC in the region.

The less dependence of EPC on NTL as compared to previous year can also be attributed to the increase in dependence of EPC on other factors like COVID cases reported in that region, mobility observed in various sectors etc. This has clearly been reflected from our study by correlating the multidomain datasets with EPC along with NTL during lockdown period. Hence, it can be concluded that the total EPC in the region is not directly dependent entirely on NTL but is also influenced by factors arising due to COVID-19 in the year 2020. Thus, a complex relationship between EPC and NTL along with other factors related to COVID-19 prevails for the lockdown scenario.

4.4.3 Results of correlating the multi-domain datasets during COVID-19 lockdown

The correlation between various variables considered for our study is calculated using Pearson's correlation method. For this the percentage deviation from baseline is considered for mobility, NTL and EPC data whereas absolute values of COVID cases data are taken. The moving averages of these datasets is considered with a window size of
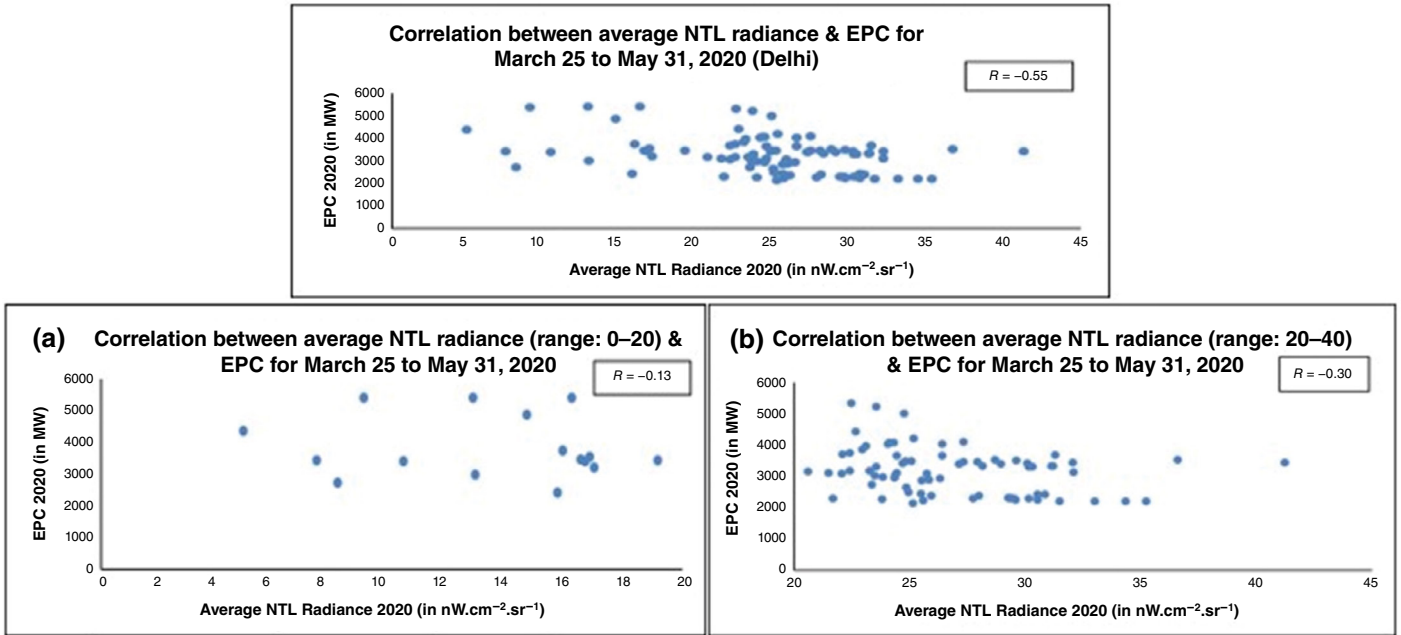
FIG. 4.10 Correlation of NTL and EPC for 2020 with radiance values categorized as (a) full range 0-40 (b) range 0-20 (Residential) (c) 20-40 (transit stations, parks, workplaces, & other commercial sectors).

12 days. The pairwise correlation between each variable gives insight on how strong or weak the association between the variables is. The results of R ranging from -1 to 1 have been tabulated in Table 4.1. The main inferences are:

- There is a strong positive correlation of 0.786 between percentage deviation from baseline in NTL and mobility seen in parks. This might be because luminance in parks and common areas directly correlates to human mobility in these areas. With increased stay-at-home practices, lighting of parks and common areas for safety of children, women and families strolling at night, could be a reason.
- The NTL shows weak positive correlation with the mobility in residential areas which is obvious as the indoors lights are not usually a good measure of NTL captured from the satellite imagery.
- The deviation in EPC has shown high positive correlation with deviation in mobility at workplaces and transit stations. During the lockdown, the mobility in these areas was highly restricted, therefore mobility and EPC have both reduced drastically; leading to a higher positive correlation value.

TABLE 4.1 Pairwise Correlation between each variable using Pearson's method

Pearson's correlation, R	Confirmed cases	Deceased cases	NTL deviation	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential	EPC deviation
Confirmed cases	1.000									
Deceased cases	0.756	1.000								
NTL deviation	−0.605	−0.406	1.000							
Retail and recreation	0.800	0.722	−0.281	1.000						
Grocery and pharmacy	0.891	0.694	−0.622	0.848	1.000					
Parks	−0.404	−0.138	0.786	0.007	−0.499	1.000				
Transit stations	0.895	0.705	−0.619	0.873	0.997	−0.466	1.000			
Workplaces	0.891	0.725	−0.567	0.922	0.977	−0.362	0.989	1.000		
Residential	−0.848	−0.715	0.459	−0.957	−0.935	0.227	−0.955	−0.986	1.000	
EPC deviation	0.886	0.661	−0.727	0.768	0.982	−0.610	0.978	0.948	−0.890	1.000

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- The correlation between EPC and NTL was found to be a relatively high negative value (–0.727), showing an inverse relationship between the two. This might be because of the dataset considered for EPC which does not provide any insights on where the electricity consumed is from luminous or indoor appliances.
- Another inference drawn from the correlation results obtained is that the NTL and confirmed COVID cases shows a negative correlation of –0.605 and between deaths due to COVID-19 and NTL is –0.406. The more there is spread of COVID-19, the less outdoor lights are captured; implying that days when more COVID cases were reported, people tend to move lesser on those nights, leading to lower outdoor NTL.

4.4.4 Results for regression-based approach for prediction of EPC

The processed EPC data along with other datasets during COVID-19 lockdown period is then used to fit a model equation for predicting future EPC after COVID-19 lockdown months. The Eq. 4.1 is obtained as the model equation for EPC.

$$EPC_{\text{modelled}} = 232 - 0.268NTL - 0.000992GP^2 \tag{4.1}$$

where,

EPC_{modelled} = percentage deviation of EPC from baseline
NTL = percentage deviation of NTL from baseline
GP = percentage deviation of mobility in Grocery and Pharmacy, from baseline

The modelled Eq. (4.1) is in line with (Sahoo et al., 2020) which also predicted that EPC can be modelled using NTL. The model Eq. (4.1) obtained has a mean absolute error, MAE = 11.536 with goodness of fit (coefficient of determination) $R^2 = 0.988$. In Eureqa, the complexity of the model equation indicates the complexity of the terms used to build equation while fit is a standardized metric which decreases as the accuracy of the model equation increases. We see that the obtained model Eq. (4.1) of EPC not only depends on NTL but also has a factor of GP^2 which is the mobility in sectors of grocery and pharmacy. This proves our hypothesis that the EPC during COVID-19 lockdown depends on other factors prevailing during COVID-19 lockdown, along with NTL. This gives us an insight that the future predictions on EPC can be done by considering the factor of mobility in commercial areas like pharmacies, etc., and not just on NTL. This can be helpful for policy makers responsible for optimal distribution of electric power within a state.

Eureqa generates all possible model equations for EPC. Equations containing more independent variables (such as mobility in residential areas, transit stations etc. and COVID cases) were also generated. However, the weightage assigned to them was very low. Therefore Eq. (4.2) was selected which had the two most important variables (NTL and mobility in grocery and parks). This made the model more understandable and fit-for-purpose. This equation also proves our hypothesis that the EPC during lockdown has an impact of other ancillary variables like mobility in various sectors along with NTL. For further validation of our hypothesis, accuracy assessment can be done for the predicted results obtained through modelled equation to the actual data, as discussed in recommendations.

4.5 Conclusions and recommendations

This study explores the changes in NTL during COVID-19 lockdown and studies its impact on the electricity sector in Delhi. This can be concluded from our study, that the correlation between EPC and NTL has been impacted during lockdown months from March 25, 2020 to May 31, 2020. As we compare the correlation of NTL and EPC for the same period in 2019, there seems to be a high positive correlation for NTL < 20 nW.cm^{-2}.sr^{-1} for low lit residential areas and high negative correlation for NTL > 20 nW.cm^{-2}.sr^{-1} for high lit commercial areas. This correlation ceases to exist for the lockdown months of 2020 where there is weak correlation between NTL and EPC for both the ranges. This decrease in dependence of EPC on NTL can be attributed to the impact of other variables like mobility and COVID cases on the EPC during lockdown months. For further insights on this, the correlation between multidomain dataset is studied. Various approaches are adopted to harmonize the multidomain datasets, temporally, spatially, and quantitatively like expressing dataset as percentage change in deviation from baselines, taking median of NTL to bring to state-level, considering moving averaged data with a window size of 12 days (which is in sync with the incubation period of COVID-19). The multidomain correlation results give insights on the relationship of each variable with other variables during the lockdown period. A high positive correlation between EPC and mobility in retail and recreation sectors, grocery and pharmacy sectors, etc., is seen which

corresponds to the dependence of EPC on these variables. The negative high correlation is also seen between NTL and EPC. But this can be due to the nonavailability of breakup of electricity sector data into various sectors of consumption. Finally, a model equation is obtained using symbolical regression-based approach where the modelled EPC is expressed as a function of NTL and also depends on the second order of percentage change in deviation from baseline in mobility for grocery and pharmacy stores. This model equation can be used to conclude that the EPC during COVID-19 lockdown is not just dependent on NTL but is also impacted by other factors like mobility.

In the future work the following points are recommended for getting improved results:

- The EPC data from POSOCO being considered in our analysis, does not give a breakup of electric power consumed in various sectors like residential, commercial, public places etc. For better analysis and correlation results, a dataset, which categorizes the consumption based on different sectors, can be used.
- While studying the correlation between multidomain dataset, the NTL data has been considered as a single value brought to the state level by taking median of lights from percentage change in deviation from baselines. If the radiance values of NTL are categorized in various ranges as discussed in Section 4.2, better insights on the correlation between different variables can be obtained.
- The model equation for prediction of EPC for post COVID scenario can be obtained considering more complex terms for accurate predictions. Because of limited time for the study, a simple equation was considered which proved our hypothesis. Also, accuracy assessment for the predicted results should be included for further validation of the modelled equation.
- The mobility dataset made available from Google gives a lumped categorical value of temporal deviation for each Indian state. The spatially distributed geometries which are used to construct these categorical mobility deviations, if provided, can help expand this study to obtain more "spatial" results.

Acknowledgements

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