

# Social Impact Analysis Using NTL (Night Time Light) Data On Various Socio - Economic Factors

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**Abstract** -This research paper delves into the application of Nighttime Light (NTL) data as a powerful tool for conducting Social Impact Analysis across diverse socio-economic factors. With the advent of satellite-based technology, NTL data has emerged as a valuable resource for assessing and understanding the dynamics of human activities and development. The study employs a multidisciplinary approach, integrating geospatial analysis and socio-economic indicators to examine the intricate relationships between NTL and various aspects of societal well-being. The methodology involves the collection and processing of NTL imagery, utilizing advanced remote sensing techniques to quantify and analyze the intensity of artificial lighting. The research explores the correlation between NTL and critical socio-economic parameters such as urbanization, economic growth, migration, and per capita power consumption. Additionally, it investigates the potential of NTL data in capturing patterns related to infrastructure development, human migration, and environmental changes. Furthermore, the paper

discusses the implications of the findings for policymakers, urban planners, and researchers in enhancing evidence-based decision-making processes. By leveraging NTL data, this research aims to contribute to a more comprehensive understanding of the social impact of human activities on a global scale. Ultimately, the study advocates for the integration of NTL data into socio-economic analyses, promoting informed and targeted interventions to address pressing societal challenges.

**Index Terms**—Nighttime Light (NTL) data, social impact analysis, socio-economic factors, urbanization, economic growth, infrastructure development, human migration, environmental changes, policymakers, urban planners, researchers

## I INTRODUCTION

In an era marked by rapid urbanization, economic transformations, and global interconnectedness, the quest to comprehend the intricate fabric of socio-

economic dynamics has become increasingly complex. Unraveling the nuances of societal well-being necessitates innovative approaches that can capture the multifaceted interactions between human activities and development. This research embarks on a journey into the realm of Social Impact Analysis, employing Nighttime Light (NTL) data as a novel and potent instrument for exploring a myriad of socio-economic factors. As artificial lighting patterns illuminate the Earth's surface, satellite-based technology, in the form of NTL imagery, has emerged as a valuable lens through which to scrutinize the consequences of human endeavors. The integration of geospatial analysis and socio-economic indicators not only presents an opportunity to decipher the impact of urbanization, economic growth, poverty, and inequality but also unveils hidden patterns related to infrastructure development, human migration, and environmental changes. In this context, the forthcoming exploration aims to shed light on the transformative potential of NTL data, advocating for its incorporation into the arsenal of tools empowering policymakers, urban planners, and researchers in their pursuit of informed and effective societal interventions.

## II. KEY FINDINGS

**Electrification Impact on Socio-Economic Factors:** The comprehensive analysis of rural electrification reveals a positive correlation between the increase in electrification [2] and various socio-economic indicators [3]. The literacy rates in electrified rural areas have shown a commendable rise [4][5], suggesting a direct link between electrification and educational outcomes [6].

**State-Level GDP Dynamics:** Quarterly analysis performance underscores its economic vitality, showcasing consistent growth trends. The state's GDP has not only demonstrated resilience but has also significantly contributed to the national economic landscape.

### **Interconnected Social and Economic:-**

**Dynamics:** A nuanced analysis of trends and relationships among electrification, education, agriculture, and economic conditions provides a comprehensive understanding of the intricate social and economic dynamics [7][8].

## **Assessment of Urbanization and Infrastructure:**

Urbanization trends reveal a steady increase in urban population, accompanied by corresponding infrastructure growth. The expansion of urban areas is contributing to enhanced connectivity, improved living standards, and increased economic activities [9][10].

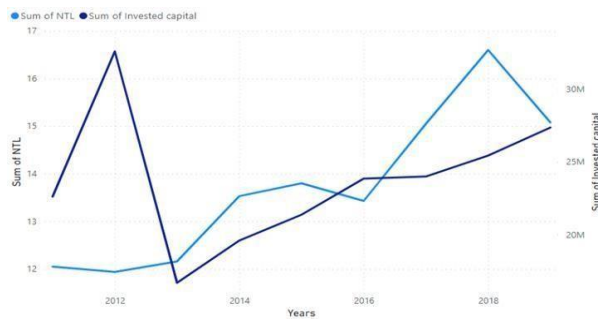
## III. NTL DATA FOR INDIA (2012-2021)

This research has collected and analyzed a substantial amount of data from open-source, global trustworthy resources [9][11][12] as well as of India, including the RBI Handbook of Statistics on Indian Economy, various government portals, and the Bhuvan portal of ISRO. The gathered NTL data provides convincing correlation of NTL with the mentioned socio-economic parameters. The relationships are displayed by constructing graphs of NTL vs the given social parameter throughout the years 2012-2021. The trends and fluctuations of the NTL curve in the graph correspond highly with the behavior and variations of the social factor, enabling the determination of the possibilities that lead to the change in these socio-economic factors [12][13].

## IV. ANALYSIS OF SOCIAL PARAMETERS FOR THE STATES OF ANDHRA PRADESH AND TELANGANA

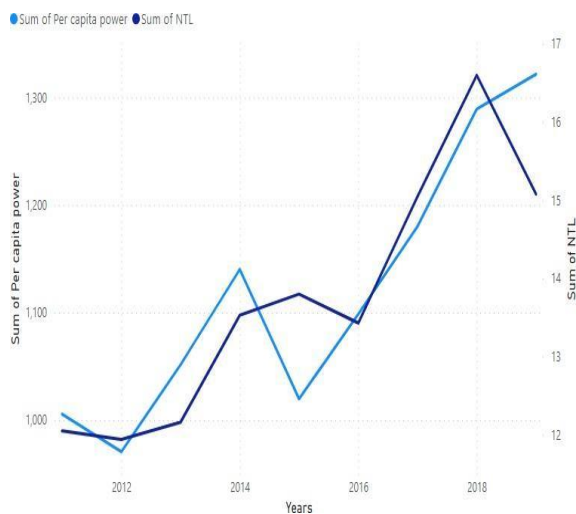
### **Andhra Pradesh:**

**NTL vs Invested Capital:** Upon a detailed examination of the data, a discernible pattern emerges, revealing a positive correlation between NTL and Invested Capital. As NTL increases, there is a concurrent upward trajectory observed in the Invested Capital. The year 2014 marks a distinct event that influenced the financial landscape—The Andhra Pradesh Reorganisation Act, leading to the separation of two states. This legislative change had a discernible impact on the observed NTL versus Invested Capital graph, causing a slight dip in the relationship between the two variables. The separation likely triggered adjustments in financial structures, affecting both liabilities and capital allocation. **Post-2014 Recovery:** Post the initial dip in 2014, the subsequent years portray a resilient recovery and a pronounced increase in the correlation between NTL and Invested Capital.



**Figure 1: NTL and Invested Capital over years (AP)**

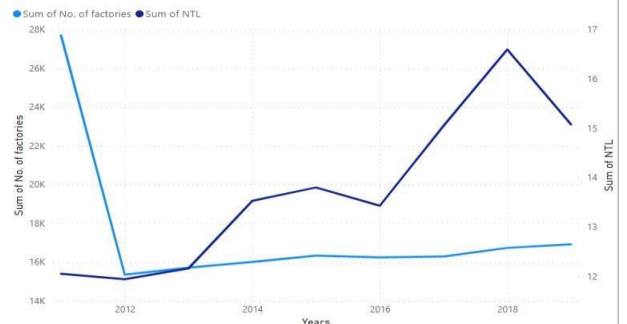
**NTL vs Per Capita Power:** The graph shares a nearly synonymous relationship of NTL with Power consumed per capita in the state of Andhra Pradesh. The capita shows a steady elevation until 2014, where, due to the Andhra Pradesh Reorganization Act, a significant decline in the graph is observed for both the Capita line and slightly for the NTL line. However, the graph recoups its elevation course after 2014 as can be seen by a farther associative curve of NTL because of several development factors undergoing in the region.



**Figure 2: NTL and per capita power over years (AP)**

**NTL vs Number of Factories:** The above graph shows the No. of factories vs NTL data. Through this comparison, we can find the relationship between the number of factories opened and the impact of NTL on Factories. The Graph begins with a decline in No. of factories before 2012 in the state. Possible reasons were due to communal and economic fluctuations. Since then, a frugal increase of almost 200 factories

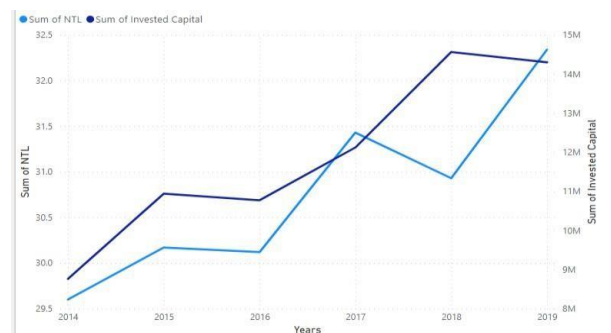
per year has been recorded with a heavy increase in light pollution; the awareness of which led to a substantial fall in NTL sum by choosing the optimal lighting conditions in factories by the concerned authorities to tackle this problem of light pollution.



**Figure 3: NTL and Factories over years (AP)**

**A. Telangana:**

**NTL vs Invested Capital:** There has been a drastic equivalence of NTL growth with respect to the Invested Capital in Telangana. As the invested capital has climbed, stabilized, and dipped, so has the NTL data along with it. The intersections of the two curves can be observed near the 2017 era. However, a dip afterward suggests that light pollution controlling policies have been implemented, causing a deviation of investment and NTL. The inevitable growth of the state further remains to diminish this deviation.



**Figure 4: NTL and Invested Capital over years (Telangana)**

**NTL vs Per Capita Power:** The upward trend in the graph of Sum of per capita power and Sum of NTL throughout the years 2014-2019 suggests that power consumption has been promulgated thoroughly in the region of Telangana. Constant activities of industries, residences, and offices have supplied the elevating

trend of NTL and indicate the extension of cost in electricity.

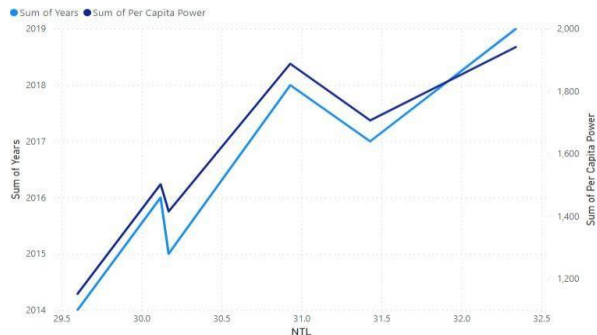


Figure 5: NTL and Per Capita over years (Telangana)

**NTL vs Number of Factories:** Telangana has achieved tremendous growth in the sum of the number of factories right after 2014 thanks to the various economic policies brought forward by the government. The sum of NTL data corresponds with this increase, and the incessant implementation of excellent lighting systems and regional development due to factories further brings the NTL data to coincide with the number of factories.

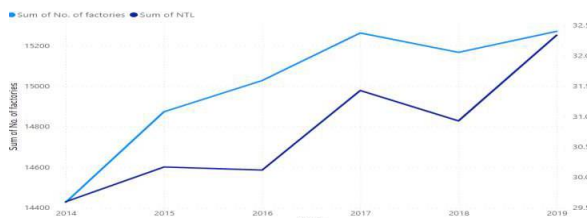


Figure 6: NTL and Factories over years (Telangana)

## V. SCOPE OF THE ANALYSIS

**Urbanization and Economic Development:** Correlate NTL data with GDP, employment rates, and other economic indicators to understand the impact of urbanization on local economies.

**Infrastructure Development:** Use time-series NTL data to track the impact of major infrastructure projects on local development, such as the construction of highways, airports, or power plants[15].

**Impact of Natural Disasters:** Analyze the relationship between NTL decline and factors such as economic losses, displacement, and post-disaster recovery rates.

**Agricultural Productivity:** The correlation between NTL intensity and agricultural output, identifying regions where changes in farming practices have socio-economic implications.

**Education and Literacy:** Correlate NTL data with education indicators, such as school enrollment rates and literacy levels, to identify areas with educational challenges.

## VI. CONCLUSION

In conclusion, the utilization of Nighttime Lights (NTL) data has proven to be instrumental in assessing and understanding the economic development and socio-economic landscape of Andhra Pradesh and Telangana[16]. The observed correlation between NTL intensity and key indicators such as electrification status, agricultural productivity, and overall development underscores the significance of this data in measuring progress and identifying areas for improvement.

NTL data not only reflects the electrification status of a region but also serves as a proxy for economic growth and investment attractiveness[13][14]. The presence of higher NTL rates indicates increased economic activities, job opportunities, and advancements in sectors like agriculture, education, and industry.

Furthermore, the ability to analyze NTL fluctuations in response to natural disasters provides valuable insights into disaster impact and post-disaster recovery rates. This information is essential for effective disaster management and resilience planning.

In summary, NTL data is a powerful tool that enables policymakers, researchers, and stakeholders to make informed decisions, allocate resources efficiently, and drive sustainable development in Andhra Pradesh and Telangana. Its continued utilization and integration

into development strategies will further contribute to the advancement and prosperity of these regions.

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