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Mapping Urban Extent Associated with Socioeconomic Modelling from VIIRS/DNB Data and Landsat Imagery

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Abstract: This research paper introduces a novel approach for estimating Gross Domestic Product (GDP) in the National Capital Region (NCR) of Delhi using remote sensing data. The study utilizes night-time light data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) to investigate the relationship between urbanization and GDP in the region. Land Use Land Cover (LULC) changes were analyzed using Landsat data for the years 1998, 2008, and 2018, while VIIRS/DNB data was employed to extract urban areas for the years 2012, 2015, 2018, and 2021. GDP estimates for NCR Delhi were derived from state-wise statistics of Delhi, Uttar Pradesh, and Haryana for the years 2012 to 2021. The analysis reveals a statistically significant correlation between urban area growth and GDP growth in the Delhi NCR. Regression analysis is employed to establish the relationship between GDP and night time light data, resulting in the prediction of an estimated GDP of 1,02,00,000 million INR for the year 2023. This study demonstrates the potential of remote sensing data for estimating socioeconomic indicators and provides valuable insights into the changing landscape of the Delhi NCR.

Keywords: night-time light data; urbanization growth; socio economic indicator, GDP, Regression analysis

1. Introduction

Urban areas worldwide exhibit a distinct increase in night light intensity due to the presence of elements such as streetlights, shops, industries, and residential areas. This phenomenon signifies the human socioeconomic activity within these regions, making nighttime lights a potential indicator correlated with various socioeconomic factors. The utilization of remote sensing satellite imagery has greatly contributed to urban area mapping and urbanization monitoring, providing real-time data sources for comprehensive analysis. Notably, the extraction of urban extent at regional and international scales has been successfully achieved through the use of coarse-resolution imagery, such as night-time light (NTL) data[1)]. NTL imagery encompasses the captured views of the Earth's surface during clear nights by remote sensing sensors. Unlike the brightness captured during daylight, the NTL images vividly depict the illumination generated by city lights, which directly reflects human activity. Consequently, NTL data offers unique insights for socioeconomic studies and has found extensive usage in disciplines such as regional economics[2)], and urbanization research[3,4)]. The Day-Night Band (DNB) in the Visible Infrared Imaging Radiometer Suite (VIIRS) aboard the Suomi National Polar-orbiting Partnership Satellite and the Operational Linescan System (DMSP/OLS) data from the Defense Meteorological Satellite Program are two widely employed sources of NTL data[5)].

In the realm of urban extent extraction using NTL data, three primary techniques are commonly employed: thresholding-based, classification-based, and index-based approaches[6–8)]. The multiple-threshold approach is frequently favored due to its ability to handle the diverse range of urban development stages. To identify potential urban clusters, a logistic regression model is often utilized, and suitable thresholds are determined based on cluster size and total NTL magnitude[9]. This approach effectively maps urban regions by clustering the NTL data. On the other hand, the classification-based approach treats NTL data as grayscale images and applies various classification methods to identify urban areas[10]. Although significant prior knowledge is typically unavailable, the selection of appropriate training samples greatly influences the accuracy of the classification technique. These different extraction techniques provide valuable tools for analyzing and mapping urban extents using NTL data, allowing for comprehensive studies of urbanization patterns and trends. By employing appropriate methodologies, we can gain insights into the socioeconomic dynamics and spatial distribution of urban areas, contributing to informed decision-making processes and sustainable urban development strategies.

In this study, we aim to explore the precise correlation between urban growth and a key socioeconomic indicator, Gross Domestic Product (GDP). Traditional approaches for estimating GDP rely on surveys and administrative data, which are often time-consuming and expensive[11]. However, in recent years, remote sensing data has emerged as a promising alternative for estimating socioeconomic indicators. We introduce a novel approach for estimating GDP specifically in the National Capital Region (NCR) of India, utilizing remote sensing data. By leveraging the power of remote sensing, we aim to provide a unique and accurate estimation of the economic activity within the region. This method offers potential advantages in terms of efficiency, cost-effectiveness, and the ability to capture valuable insights into the economic dynamics of the NCR Delhi.

To achieve our objectives, we analyze night-time light data from VIIRS/DNB to study the relationship between urbanization and GDP in the Delhi NCR. We extract urban areas and analyze Land Use Land Cover (LULC) changes using Landsat data. By examining the growth of urban clusters and establishing a mathematical relationship between night-time light brightness and GDP over the years, we can predict the GDP for 2023 using brightness data when GDP data is not yet available.

Our findings reveal a statistically significant correlation between urban area growth and GDP growth in the Delhi NCR. Through regression analysis, we establish a relationship between GDP and VIIRS/DNB data, enabling the estimation of GDP for 2023. The results demonstrate the potential of remote sensing data in estimating socioeconomic indicators and provide valuable insights into the changing landscape of the Delhi NCR using Landsat data for the years 1998, 2008, and 2018. VIIRS/DNB data was used to extract urban areas for the years 2012, 2015, 2018, and 2021.

The remainder of the article is structured as follows: Section 2 provides an overview of the study area. Section 3 describes the materials used in this study. Section 4 outlines the methods used for data analysis, including SVM supervised classification and accuracy assessment. Section 5 presents the results of the study, including LULC changes, urban area extraction, and the relationship between urbanization and GDP. Section 6 discusses the implications of these results and offers prospects for the future. Finally, Section 7 concludes the article with a summary of the key findings and their relevance for sustainable development policies in Delhi NCR.

2. Study area

The study area for this research is the NCR, located in northern India. The Delhi NCR includes parts of three states: Delhi, Uttar Pradesh, and Haryana. Specifically, it comprises two districts of Uttar Pradesh (Gautam Buddha Nagar and Ghaziabad) and two districts of Haryana (Gurugram and Faridabad). The population of the Delhi NCR constituents, according to the Census of India 2011, is as follows: Delhi NCT (16,787,941), Gurugram (1,514,085), Faridabad (1,809,733), Gautam Buddha Nagar (1,648,115), and Ghaziabad (1,648,643). The study area was located between latitudes 27°45'0" N to 29°0'0" N and longitudes 76°45'0" E to 78°15'0" E (Fig.1). The Delhi NCR has a total area of 7,930 km2 and is geographically situated between the Himalayas in the north and the Aravalis in the south. The Yamuna River flows through the middle of the region. These cities within the Delhi NCR are highly developed and densely populated, experiencing rapid industrialization, urbanization, and socioeconomic growth[12–14]. However, the region also faces significant challenges, particularly in terms of air pollution. The rapid development has led to severe air pollution, with Delhi being the most polluted city in the Delhi NCR. Addressing air pollution and maintaining safe and healthy air quality has become a crucial concern for the region[15–17]. Given its diverse physical surroundings and varying levels of socioeconomic development, Delhi NCR serves as an ideal location to compare and assess the effectiveness of different urban area mapping techniques using nighttime light data. The research aims to utilize remote sensing data to gain insights into the urbanization patterns, socioeconomic dynamics, and environmental challenges in the Delhi NCR.

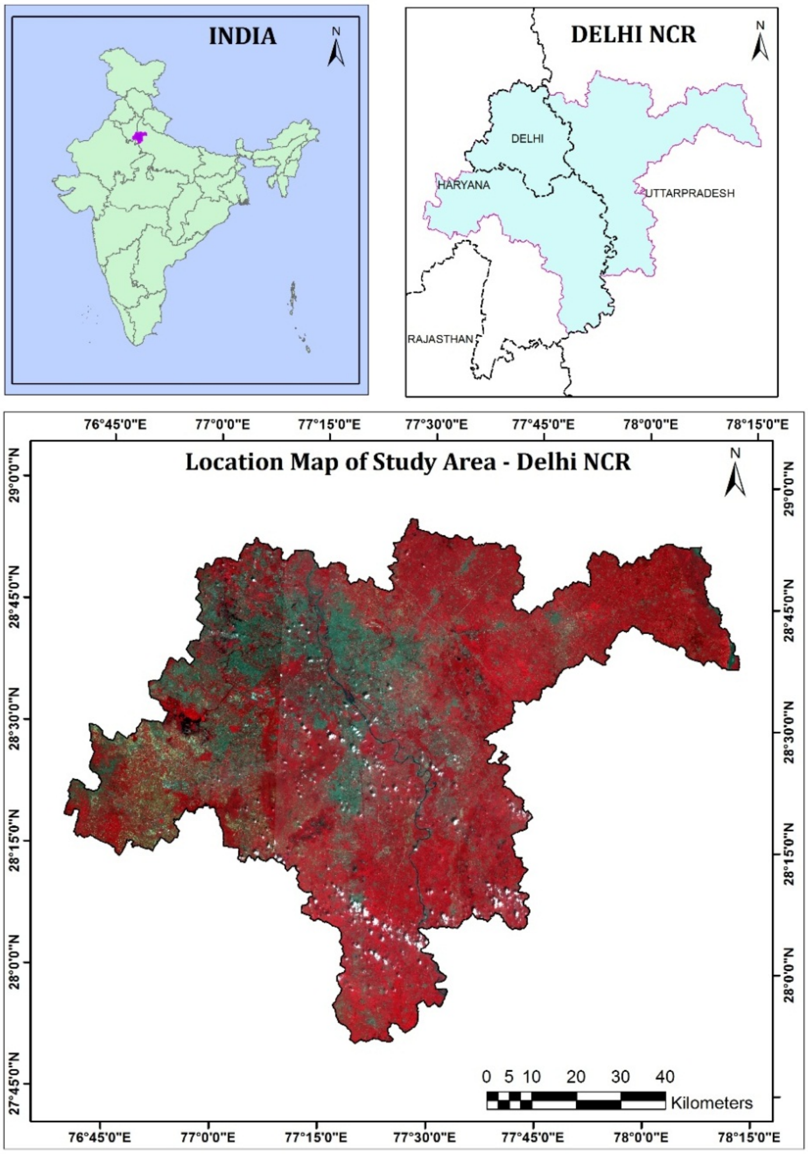


Fig.1: Location of the study area

3. Materials

3.1.VIIRS/DNB data

The NOAA VIIRS is used to generate global night-time light products, but it faces challenges related to stray light from the Sun and other sources. To mitigate these issues, specific procedures are followed to eliminate background noise, solar and lunar contamination, and other unrelated sources. Despite improvements over the previous DMSP/OLS system, VIIRS/DNB still struggles with the day-night terminator and data gaps. To address this, a suggested approach combines exponential smoothing and gap correction techniques, resulting in improved predictions of annual economic activity. Furthermore, developing an algorithm capable of identifying low stratus and fog in NPP/VIIRS imagery is crucial. This algorithm should consider observation geometry, radiative transfer modeling, and multiple data channels. By incorporating these factors, the algorithm can accurately distinguish instances of low stratus and fog. Enhancing the quality of VIIRS/DNB data is essential for understanding the relationship between night-time light intensity and socioeconomic factors, providing insights into urbanization patterns and their environmental impact.

3.2.Landsat data

Landsat 5 for March 1998, Landsat 5 for April 2008, and Landsat 8 for April 2018 were obtained for the research area. The data was downloaded from the United States Geological Survey (USGS) Earth Explorer website. The Landsat 5 and Landsat 8 data products, also known as surface reflectance products, provide an estimation of the surface spectral reflectance at a spatial resolution of 15 meters and 30 meters respectively. These products are useful for analyzing the reflectance properties of the Earth's surface without the influence of air scattering or absorption. For this study, the nearest cloud-free image was selected had partial cloud cover. For extracting urban areas and analyzing urbanization patterns, both supervised and unsupervised methods were employed. The supervised method involved the use of training samples to classify the land cover into different categories, including urban areas. On the other hand, the unsupervised method utilized clustering algorithms to automatically identify and classify different land cover types. We aimed to accurately analyze and map the urban extent in the study area by comparing the effectiveness of these two methods. By employing both supervised and unsupervised methods with the Landsat 5 and Landsat 8 data, a comprehensive understanding of urbanization patterns in the research area was achieved.

4. Methodology

4.1 Land Use Land Cover Classification

In Fig. 2, the classified images of Delhi NCR for the years 1998, 2008, and 2018 are shown, depicting the distribution of the five different LULC classes: barren land, built-up land, cropland/agriculture, plantations/forest, and water bodies. These images provide a visual representation of the changes that have occurred in the land cover of Delhi NCR over the span of 20 years. Table 1 presents the percentage distribution of each LULC class in Delhi NCR for the years 1998, 2008, and 2018[18]. The values in the table indicate the proportion of each land cover class within the region during the respective years.

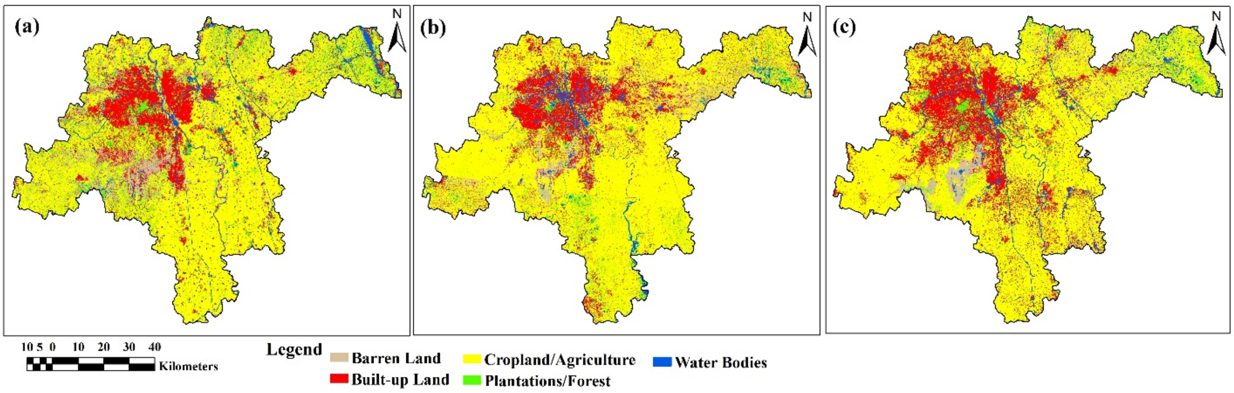


Fig. 2: Land Use Land Cover (LULC) change in Delhi NCR for the years (a) 1998, (b) 2008, and (c) 2018

Table 1: Land Use Land Cover (LULC) classes in Delhi NCR for the years 1998, 2008, and 2018

Sr. No.	LULC Classification	LULC (1998)		LULC (2008)		LULC (2018)		Change 1998-2008	Change 2008-2018
		Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Changed Area (km^2)	Changed Area (km^2)
1	Barren Land	786	9.91	499	6.29	389	4.91	-287	-110
2	Built-up Land	1215	15.32	1275	16.08	1631	20.57	60	356
3	Cropland/Agriculture	4688	59.12	5556	70.06	5367	67.68	868	-189
4	Plantations/Forest	1135	14.31	512	6.46	477	6.02	-623	-35
5	Water Bodies	106	1.34	88	1.11	66	0.83	-18	-22
Total		**7930**	**100.00**	**7930**	**100.00**	**7930**	**100.00**		

4.2 Accuracy Assessment

The effectiveness of the urban extent extraction techniques described in Section 3.2 was evaluated using a visual interpretation technique. High-resolution Google Map satellite imagery with a spatial resolution of 1 m was used as the reference or “ground truth” data. A total of 290 randomly selected locations in the research area were visually classified as either “urban regions” or “non-urban areas” based on the Google Map satellite imagery. The accuracy of the classification results was assessed using a confusion matrix, with the extracted urban areas from Section 3.2 and 4.1 serving as the “labelling findings.”

The accuracy of categorization findings is frequently described using a particular table called the confusion matrix[19]. The accuracy assessment employed several metrics based on the confusion matrix, including producer's accuracy (PA), user's accuracy (UA), overall accuracy (OA), and Kappa Coefficient (KC) equation 1, 2, 3 and 4 respectively. PA measures the likelihood of successfully detecting an urban pixel, evaluating the omission error. UA measures the likelihood of a labeled urban pixel being a true urban pixel, evaluating the commission error. KC reflects the agreement between the “labelling results” and the “ground truth” by considering both types of errors, providing a more comprehensive evaluation. OA indicates the percentage of pixels that are correctly recognized[20]. These measurements are calculated as:

$$\mathrm{PA_k} = \frac{x_{kk}}{x_{k+}} \tag{1}$$

$$\mathrm{UA_k} = \frac{X_{kk}}{X_{+k}} \tag{2}$$

$$\mathrm{OA} = \frac{\sum X_{kk}}{\mathrm{N}} \tag{3}$$

$$\mathrm{KC} = \frac{\mathrm{N}\sum X_{kk} - \sum X_{k+} + X_{+k}}{N^2 - \sum X_{k+} + X_{+k}} \tag{4}$$

where N is the total number of pixels in the dataset, X_{kk} is the number of pixels that are correctly recognised, X_{k+} is the total number of pixels that belong to class k, and X_{+k} is the total number of pixels that are identified as class k.

The confusion matrix is calculated by comparing the ground truth data with the classified image, and this process is performed for each classified image. Table 2 presents the user accuracy and producer accuracy results obtained from the classified images of Landsat-5 (1998), Landsat-5 (2008), and Landsat-8 (2018)[18]. The table also includes the overall accuracy and Kappa value for each classified image. For example, the overall accuracy for Landsat-8 (2018) was found to be 84.48%, with a Kappa value of 0.8083.

These accuracy assessment results provide insights into the performance of the classification techniques, allowing for a quantitative evaluation of their accuracy and reliability in determining urban extent.

Table 2 User Accuracy, Producer Accuracy, Overall Accuracy and Kappa Coefficient results obtained from Landsat - 5 (1998), Landsat - 5 (2008) and Landsat - 8 (2018) classified image

Class	**Landsat - 5 (1998)**		**Landsat -5 (2008)**		**Landsat - 8 (2018)**	
	User Accuracy	**Producer Accuracy**	**User Accuracy**	**Producer Accuracy**	**User Accuracy**	**Producer Accuracy**
Water Bodies	90.48%	86.36%	90.48%	88.37%	90.91%	86.96%
Cropland/Agriculture	85.71%	82.76%	86.89%	84.13%	86.67%	83.87%
Plantations/Forest	85.53%	78.31%	85.51%	78.67%	84.93%	80.52%
Built-up Land	77.63%	86.76%	79.73%	88.06%	80.82%	86.76%
Barren Land	78.38%	85.29%	79.49%	83.78%	80.00%	86.49%
	Overall Accuracy: 83.28 %		Overall Accuracy: 84.21 %		Overall Accuracy: 84.48 %	
	Kappa = 0.7923		**Kappa = 0.8033**		**Kappa = 0.8083**	

4.3 Estimating Gross Domestic Product (state) of Delhi NCR

In order to estimate the GDP of Delhi NCR, which comprises the National Capital Territory (NCT) of Delhi, two districts of Haryana state, and two districts of Uttar Pradesh state, the district-wise GDP data for Haryana and Uttar Pradesh needed to be incorporated. While the state-wise GDP data for Delhi, Haryana, and Uttar Pradesh is available in https://statisticstimes.com/economy/india-statistics, the district-wise data for Haryana and Uttar Pradesh is not available.

To estimate the GDP of the districts of Gurugram and Faridabad in Haryana and the districts of Gautam Buddha Nagar and Ghaziabad in Uttar Pradesh, a uniform rate of GDP was assumed throughout each state. The district GDP was then calculated on a pro rata basis using the geographic area of each district. The total area of Delhi NCR is calculated as 7930 km^2, with Delhi NCT covering 1484 km^2, Gurugram covering 1248 km^2, Faridabad covering 1752 km^2, Gautam Buddha Nagar covering 1415 km^2, and Ghaziabad covering 2031 km^2. The total area of Haryana is 44,212 km^2, and the total area of Uttar Pradesh is 243,286 km^2. Using this information, the estimated GDP for Haryana and Uttar Pradesh in different financial years, as well as the total GDP of Delhi NCR, has been calculated. The calculations are presented in Table 3 as follows:

Table 3 Calculation of the estimated GDP (state) of different financial years in Delhi NCR (in million INR)

Sr. No.	Financial Year	GDP (Haryana) (million INR)	GDP (Uttar Pradesh) (million INR)	GDP (NCT Delhi) (million INR)	Estimate GDP (Faridabad and Gurgaon) (million INR)	Estimate GDP (Ghaziabad and G B Nagar) (million INR)	Total GDP (million INR)
1	2011-12	29,75,390	72,40,500	34,37,980	2,01,890	1,02,560	37,42,430
2	2014-15	43,71,450	1,01,17,900	49,48,030	2,96,620	1,43,310	53,87,970
3	2017-18	64,49,630	1,41,60,060	67,79,000	4,37,640	2,00,570	74,17,210
4	2020-21	76,48,720	1,70,55,930	79,83,100	5,19,000	2,41,590	87,43,690

These estimated GDP values provide an approximation of the economic output of Delhi NCR in different financial years, considering the GDP contributions of the respective states and districts within the region.

5. Results

5.1 Land use land cover change in Delhi NCR

Different classes of changes observed in LULC within the Delhi NCR

5.1.1. Depletion of forest land and reduction of surface area of water bodies

From Table 1, it is evident that there has been a significant depletion of forest land and reduction in the surface area of water bodies in Delhi NCR over the span of 20 years.

Depletion of Forest Land: The forest cover in Delhi NCR decreased from 1135 km^2 in 1998 to 512 km^2 in 2008, representing a depletion of 623 km^2 or 54.8% in just ten years. By 2018, the forest cover further reduced to 477 km^2. The overall depletion in 20 years was 658 km^2, which accounts for approximately 58% of the original forest cover. This loss of forests has had adverse effects on air quality, biodiversity, and the overall ecosystem of the region.

Reduction of Surface Area of Water Bodies: The surface area of water bodies in Delhi NCR has shown a continuous decline over the years. In 1998, the water bodies covered an area of 106 km^2, which decreased to 88 km^2 in 2008 and further reduced to just 66 km^2 in 2018. This indicates a significant loss of 40% of the water bodies within the span of 20 years. The reduction in water bodies has serious implications for the availability of water resources in the region, considering the growing population and increasing water demand.

5.1.2. Increase of built-up area

The expansion of built-up land has been another noticeable trend in Delhi NCR, especially in the latter decade.

Steady Increase in the First Decade: Between 1998 and 2008, the built-up land increased gradually from 1215 km^2 to 1275 km^2, resulting in a growth of 60 km^2. This indicates the ongoing urbanization and development activities during that period.

Rapid Urbanization in the Next Decade: The subsequent decade, from 2008 to 2018, witnessed a steep increase in the built-up area. It expanded from 1275 km^2 to 1631 km^2, marking a significant growth of 356 km^2 or approximately 30% in just ten years. This rapid urbanization reflects the increasing pace of infrastructure development, residential and commercial construction, and population growth in the region.

The observed pattern suggests that the first decade primarily experienced deforestation and a transition towards agriculture and barren land. In contrast, the subsequent decade witnessed extensive urbanization, primarily on the previously converted agricultural land.

5.1.3. Agriculture and the pattern of transition to built-up

The LULC changes in Delhi NCR also indicate a specific pattern of transition from agricultural land to built-up areas.

Deforestation and Agricultural Expansion: The drastic reduction in forest area during the first decade was accompanied by a substantial increase in agricultural land. Between 1998 and 2008, agricultural land expanded by 868 km^2, reflecting the conversion of forested areas into agricultural activities.

Transition to Built-up Areas: The subsequent transformation of agricultural land has been observed in two ways. Firstly, agricultural land may be converted into barren patches for land plotting or other purposes. Secondly, there is a direct transition from agricultural land to built-up areas, contributing to the rapid urbanization observed in Delhi NCR.

This consistent pattern of deforestation, followed by agricultural expansion and subsequent urbanization, highlights the complex relationship between land use changes, population growth, and the expanding urban footprint in Delhi NCR.

The results of the urban extent extraction, as shown in Fig. 3, indicate a consistent increase in the built-up area in Delhi NCR over the decades of 1998-2008 and 2008-2018. This demonstrates the ongoing urbanization and development in the region. Regarding the forest and plantations, there was a significant drop in the forest area during the first decade, with almost one-third of the original area being lost. However, between the next decade (2008-2018) and the present, the forest cover has decreased only marginally. This indicates that the government has successfully implemented interventions to address the issue of deforestation and preserve the remaining forests. The subsequent paragraphs provide a detailed discussion of activities analyzing the reduction of barren land in the context of the ever-increasing population, migration, and human intervention through agricultural and construction activities. These activities likely contribute to changes in land use and can have significant implications for the environment and sustainable development in Delhi NCR.

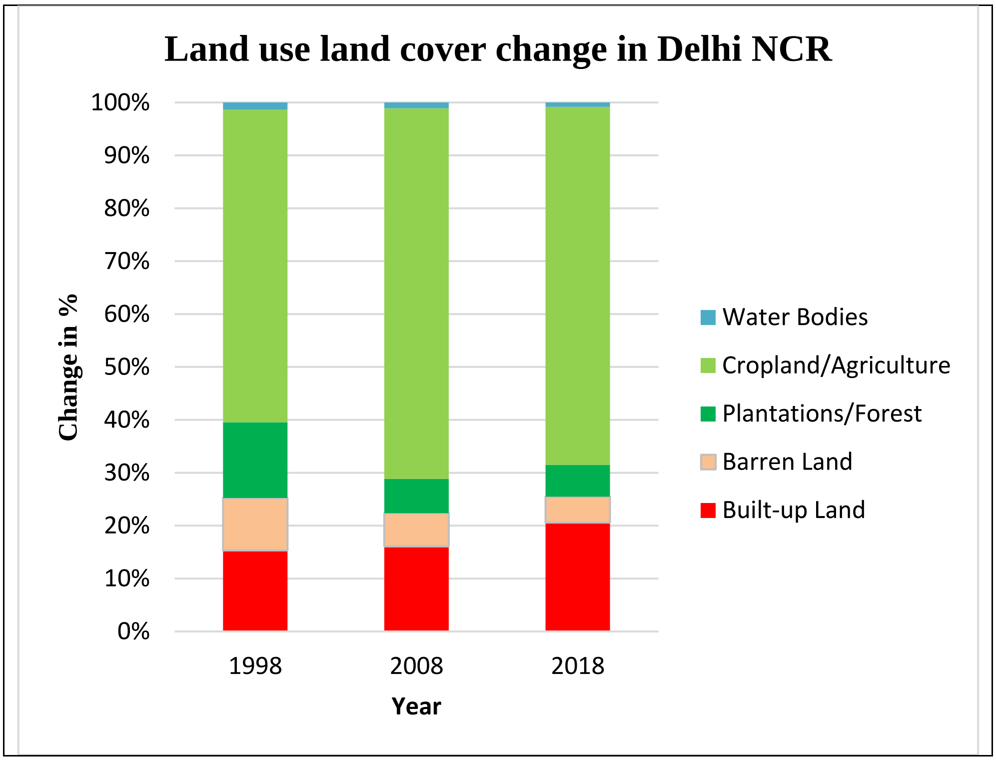
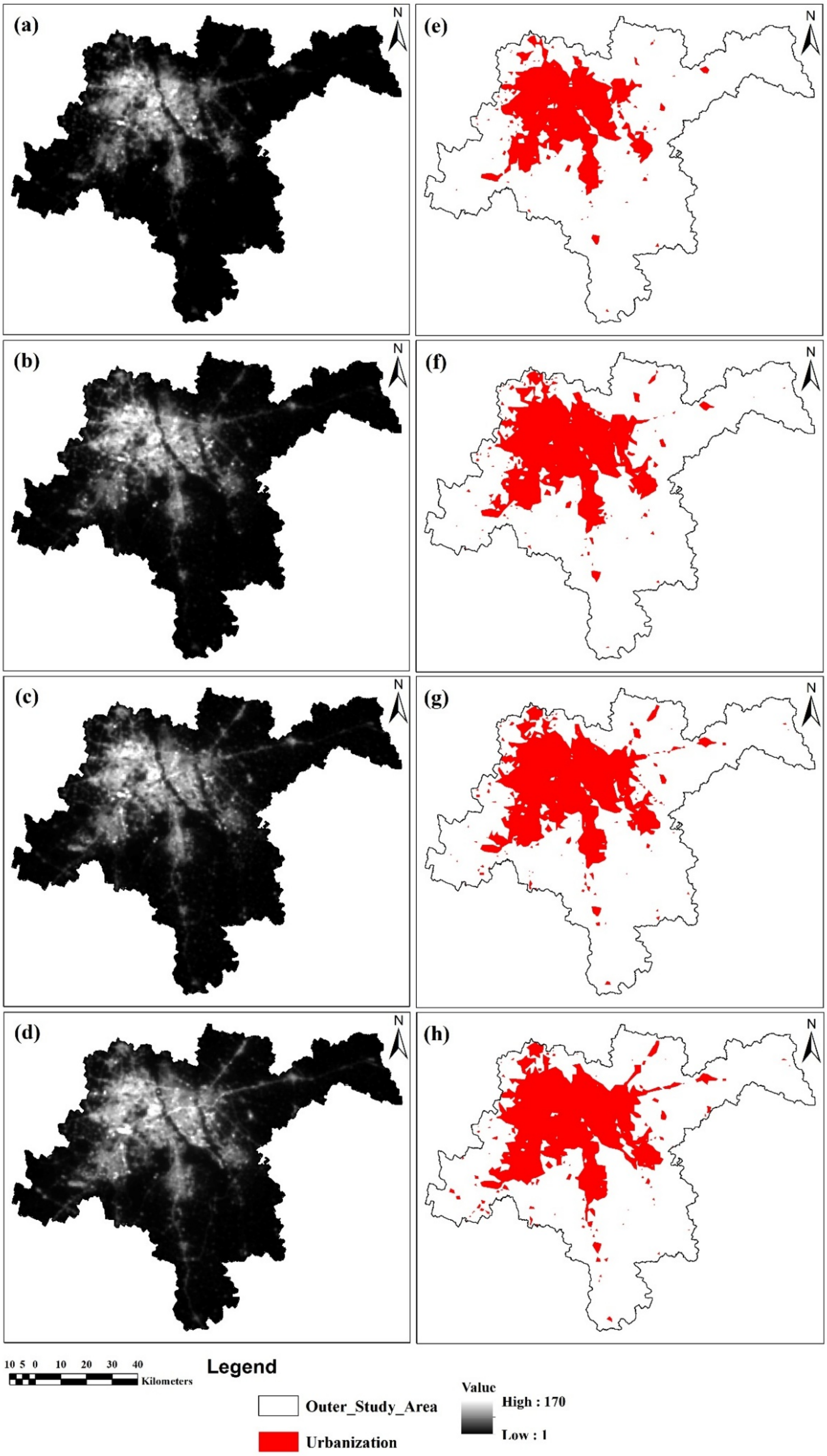


Fig. 3: Percentage of LULC change in different years (1998, 2008 and 2018) of Delhi NCR

5.2 Extraction of urban area of Delhi NCR from night-time light image

Fig. 4 presents a comparison of urban area extraction using two different methods: LULC and VIIRS/DNB data for the year 2018. The black and white composite images represent the year-wise VIIRS/DNB data, while the red images show the extracted urban areas from the corresponding black and white composite images. The overlapping of the two images indicates a similar trend of year-on-year growth in both categories. Although both methods have their advantages, the study chooses to use VIIRS/DNB data for further prediction work on GDP. The VIIRS/DNB data used in this study is a collection of average radiance composite images that have undergone processing to remove stray light, lightning, moon illumination, and cloud cover. These composite images provide high-resolution data at a geographic grid resolution of 15 arc seconds (~500m at the Equator) covering the entire planet. We downloaded the VIIRS/DNB data from the NOAA National Geophysical Data Center (https://ngdc.noaa.gov/eog/viirs/download) and focused on the area of interest (AOI) in Delhi NCR. Fig. 4 (a)-(d) displays the composite images for the years 2012, 2015, 2018, and 2021, respectively. The corresponding urbanization growth images are shown in Fig. 4 (e)-(h), indicating the expansion of urban areas over time. Night time light data captured by VIIRS/DNB is a valuable tool for analyzing urbanization and socioeconomic growth. It provides a visual representation of human activity and development during night time, with artificial light sources such as streetlights and buildings emitting visible light that has been captured by remote sensing sensors.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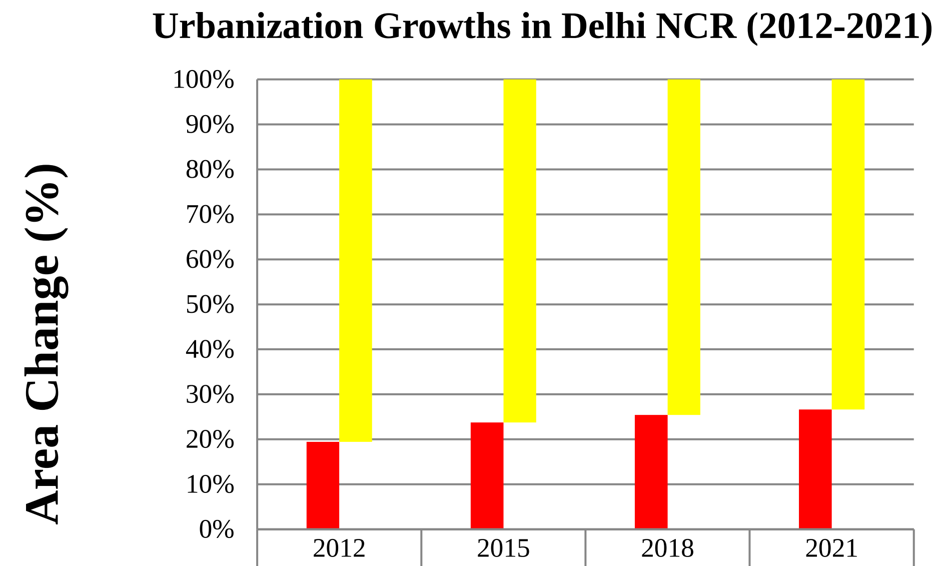
Low : 1

Fig. 4: National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP-VIIRS) Day/Night Band (DNB) average radiance composite image (a) 2012, (b) 2015, (c) 2018, (d) 2021 and urbanization growth (e) 2012, (f) 2015, (g) 2018, (h) 2021

We utilized nightlight data to study urbanization patterns. By tracking changes in the intensity and distribution of light over time, they estimated the extent of urban growth in Delhi NCR. Fig. 5 depicts a clear trend of increasing urban areas from 1545 km^2 to 2111 km^2. As cities grow and develop, they generate more light at night, resulting in a brighter and more extensive urban footprint visible from space. Analyzing time-series data of nightlight intensity allows us to monitor the growth of urban areas in the region. Nightlight data also offers insights into the relationship between urbanization and socioeconomic growth. Areas with higher economic activity and development tend to exhibit brighter night time lights due to increased energy consumption and the presence of commercial and industrial facilities. Fig. 5 demonstrates this pattern, with commercial centers in Delhi NCR appearing relatively brighter compared to residential areas. Similarly, areas with higher levels of education, income, and employment are likely to exhibit brighter night time lights.

Comparing night light data with other socioeconomic indicators such as GDP, population density, and income levels enables us to understand the factors driving urbanization and economic growth. Nightlight data can also help identify areas that lack adequate public services and infrastructure, as these areas may exhibit lower levels of night time illumination. Overall, the use of nightlight data provides a valuable tool for analyzing the spatial patterns and drivers of urbanization and socioeconomic growth in Delhi NCR.



	2012	2015	2018	2021
Non-Urbanization (Area sqkm)	6387	6048	5915	5819
Urbanization (Area sqkm)	1543	1882	2015	2111

Fig. 5: Time plots depicting relation between urbanization and non-urbanization in Delhi NCR (2012-2021)

5.3 Relationship between urbanisation and Gross Domestic Product (state) in different years

NTL data has proven to be valuable in economic research as it provides insights into variations in human activity. NTL data captures the artificial lights emitted by human activities, such as urban areas, industrial facilities, and commercial establishments, during night time hours. By analyzing changes in the intensity and distribution of night time lights, we can gain valuable information about economic trends, urbanization patterns, and socioeconomic development[21). The correlation coefficient is a statistical measure that quantifies the relationship between two variables. It measures the strength and direction of the linear association between the variables. In the context of economic research using NTL data, the correlation coefficient has been used to assess the degree of correlation between variables such as urbanization area and Gross Domestic Product[22). Fig. 6 represents the relationship between urbanization and Gross Domestic Product (state) in different years in Delhi NCR. The analysis utilized the correlation coefficient to examine the connection between the urbanization area and GDP. The calculated correlation coefficient value is 0.9587, indicating a strong correlation between the two variables. The plot in Fig. 6 visually demonstrates the concurrent increase in GDP and urbanization in Delhi NCR. Both variables are plotted to showcase the correlation between GDP growth and the expansion of the urban area, as observed in the VIIRS/DNB data. The best-fit regression curve suggests an exponential relationship, with the R^2 value reflecting the goodness of fit for GDP. The regression formula provides a mathematical representation of the relationship between the urbanization area and Gross Domestic Product (state). By examining the plot in Fig. 6, it has been inferred that as the urbanization area expands, there is a corresponding increase in the GDP of Delhi NCR.

Furthermore, the fig. 6 highlights that GDP has experienced consistent growth in comparison to the urbanized area in Delhi NCR. This suggests that urbanization has contributed to economic development and led to an increase in the region's GDP. In summary, the analysis reveals a strong positive relationship between urbanization and Gross Domestic Product (state) in Delhi NCR. The growth of the urban area is closely tied to economic progress and serves as a significant driver of GDP growth in the region.

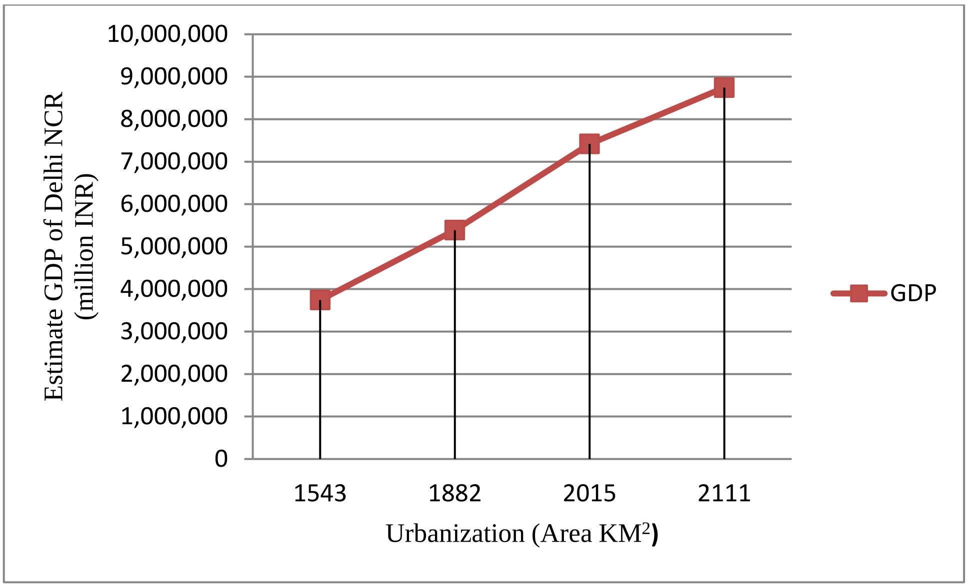


Fig. 6: Relationship between urbanisation and estimate GDP of Delhi NCR (million INR) in different years

5.4 Urban area of Delhi NCR and GDP of Delhi NCR are both correlated positively with progress of time (2012 – 2021)

The construction of a GDP spatialization data model using NPP-VIIRS-like NTL data is an important approach for estimating GDP figures. Research conducted by[23] suggests a strong correlation between NTL data and GDP. By analyzing the proportion of built-up regions located in industrial zones and considering socioeconomic factors, the relationship between these variables has been assessed. [24,25] examined the correlation between the proportion of built-up regions in industrial zones and socioeconomic factors. This analysis helps determine how closely these variables are related to each other[26]. The presence of industrial zones within built-up areas can indicate economic activity, job opportunities, and the overall development of an area. By understanding the correlation between built-up regions in industrial zones and socioeconomic factors, we can gain insights into the economic dynamics and patterns of urbanization.

Fig. 7 presents the trends of urbanization and GDP (state) in Delhi NCR from 2012 to 2021. Fig. 7 (a) shows the growth of the urban area in Delhi NCR over time. As depicted, there is a positive correlation between the urban area and time, with an R^2 value of 0.9124. This indicates that as time progresses, the urban area of Delhi NCR has been expanding. Fig. 7 (b) displays the estimated GDP of Delhi NCR plotted against the same time period. Similar to the urban area, there is a positive correlation between GDP and time, with an R^2 value of 0.9942. This suggests that the GDP of Delhi NCR has been increasing over the years. These positive correlations between the urban area and GDP and the progression of time imply that both urbanization and economic growth have been occurring in Delhi NCR. The expansion of the urban area is likely contributing to the region's economic development, as reflected by the increasing GDP.

To further investigate the relationship between the urban area and GDP, it is necessary to examine the overlap between the VIIRS/DNB data and the urban area data, as shown in Fig. 7. The blue line represents the urban area, while the red line represents the GDP of Delhi NCR. By analyzing the correlation between these two datasets, it becomes possible to determine the strength of their relationship. If a strong correlation is identified, regression analysis has been performed to predict GDP data using VIIRS/DNB data. Fig. 7 Overlap between VIIRS/DNB data and urban area data in Delhi NCR provides insights into the potential correlation between the two variables.

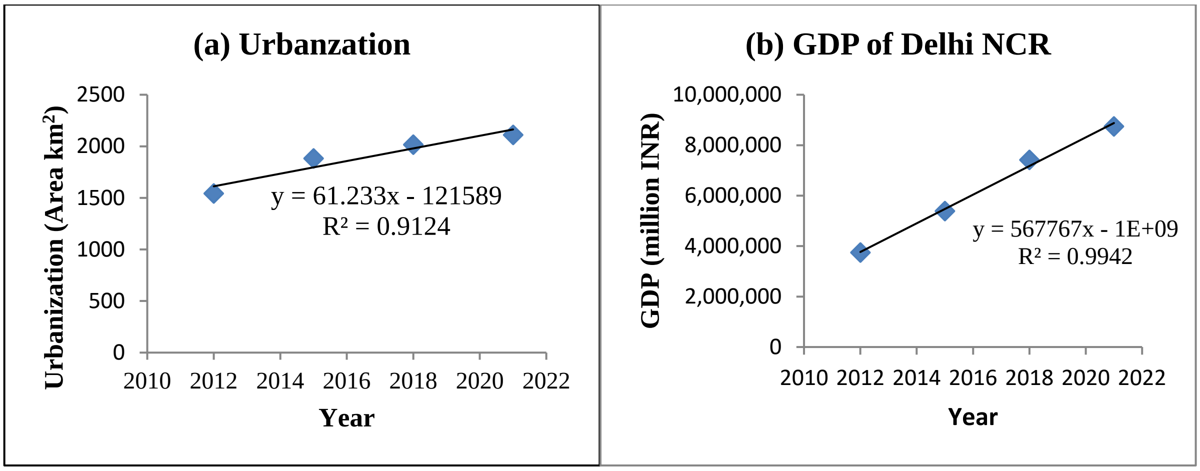


Fig. 7: Trends of change of Urbanization and GDP (state) in Delhi NCR in different years (2012-2021)

5.5 Predicting the value of GDP of Delhi NCR for 2023 using Regression on VIIRS/DNB data for 2023

The study aimed to predict the value of GDP for Delhi NCR in 2023 using regression analysis on VIIRS/DNB data of night-time light for the same year. A scatter plot was created with the values of Delhi NCR area (x-axis) for the years 2012, 2015, 2018, and 2021, and the corresponding values of VIIRS/DNB data (y-axis). Fig. 8 the scatter plot showed a clear trend, and the best fit trend line was observed to be an exponential curve. The high degree of correlation was indicated by an R^2 value of 0.9669. Based on the regression formula obtained from the analysis (Y = 365230e^0.0015x), the value of VIIRS/DNB data for the year 2023 was obtained. The difference in the Delhi NCR area between 2021 and 2023 was determined to be 132 km^2. Adjusting the regression curve by subtracting 132 from the obtained value, the GDP value for Delhi NCR in 2023 was estimated to be 1,02,00,000 million INR. This study demonstrates the potential of using remote sensing VIIRS/DNB data of night-time light products for predicting economic indicators such as GDP. By analyzing the relationship between night-time light data and GDP, it becomes possible to make estimations for future periods, providing valuable insights for planning and decision-making processes.

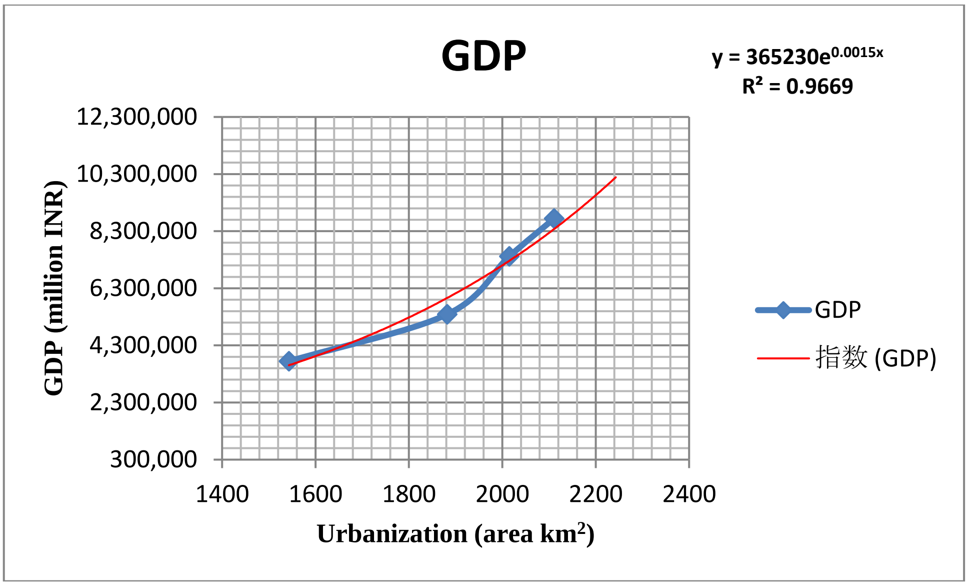


Fig. 8: Predicting the value of GDP of Delhi NCR for 2023 using VIIRS/DNB data of night-time light for 2023

6. Discussion

6.1.The Compared results Landsat data with VIIRS/DNB

The study compared the results obtained from Landsat data with VIIRS/DNB data for urban area extraction and analysis of LULC changes. Landsat data was used to extract urban areas for the years 1998, 2008, and 2018, while VIIRS/DNB data was used for the years 2012, 2015, 2018, and 2021. The comparison aimed to evaluate the benefits and limitations of using VIIRS/DNB data for assessing socioeconomic indicators. Landsat data proved to be a valuable tool for extracting urban areas and generating accurate LULC maps. The use of multispectral analysis on Landsat data facilitated the mapping of land cover types in the study region. The accuracy of the results was assessed, and the highest kappa coefficient (KC) values were identified in Table 2. These findings demonstrate the effectiveness of Landsat data for urban area extraction. In addition, the study utilized VIIRS/DNB data to analyze night time lights on an annual scale in Fig. 4 and Fig. 9 presents the LULC distribution map of Delhi NCR for the years 2012 (a) and 2022 (b), as well as the corresponding VIIRS/DNB data for the same years 2012 (c) and 2022 (d). The VIIRS data successfully identified human settlements, illuminated bridges, and roadways during night time. However, it should be noted that the urban areas extracted from VIIRS data exhibited more fragmentation, with smaller spots and some unidentified urban pixels. The comparison between Landsat data and VIIRS/DNB data highlights the strengths and weaknesses of each data source for urban area extraction and LULC analysis. While Landsat data provides accurate and detailed information, VIIRS/DNB data offers the advantage of capturing night time lights and providing insights into human activity during night time. Both datasets contribute valuable information for studying urbanization and socioeconomic indicators.

Overall, the combination of Landsat data and VIIRS/DNB data allows for a comprehensive analysis of urban areas and their changes over time, providing valuable insights for urban planning, socioeconomic research, and policy-making processes.

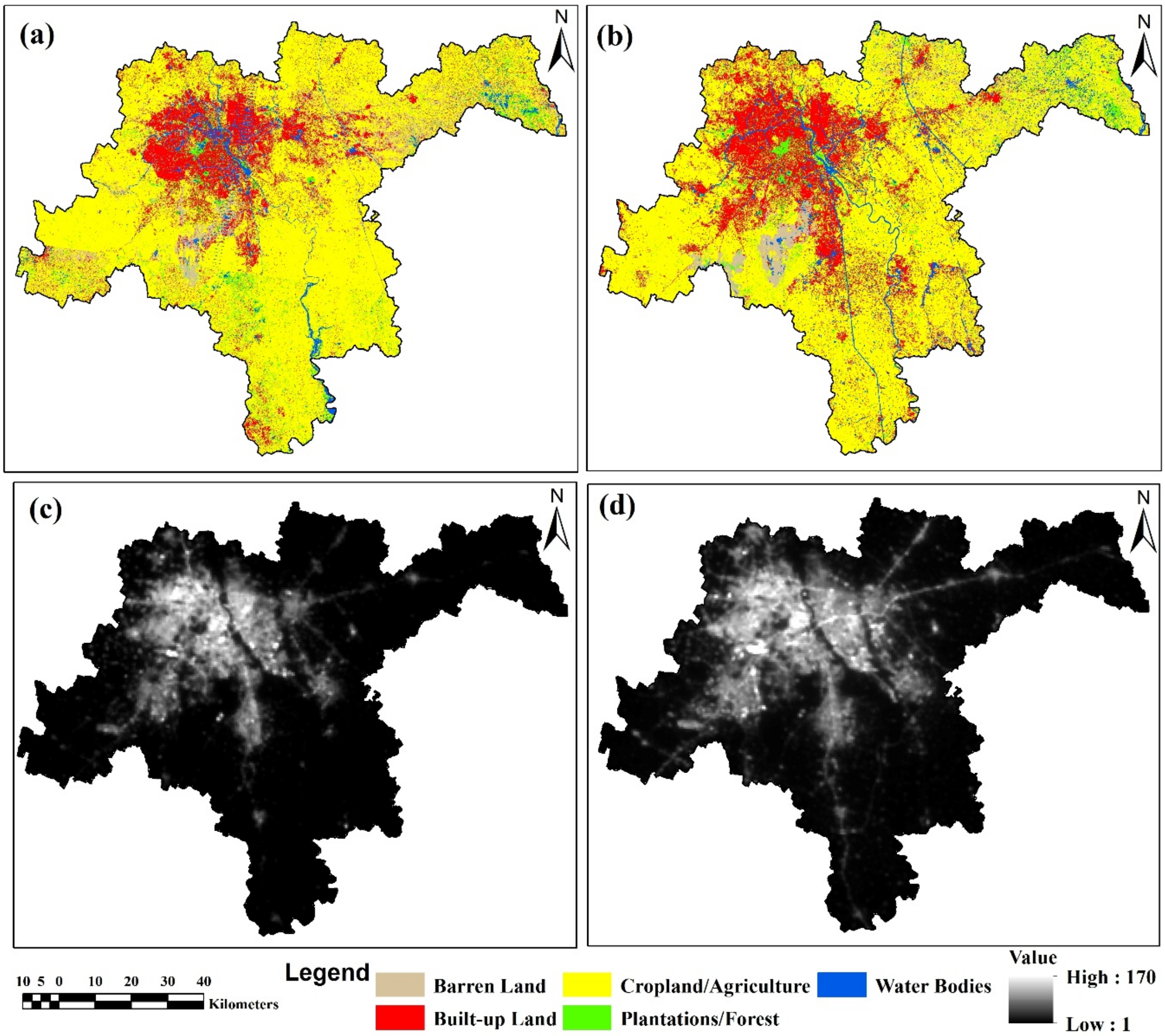


Fig. 9: LULC distribution map of Delhi NCR - (a) 2012, (b) 2022 and National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP-VIIRS) (c) 2012, (d) 2022

6.2.Prospects for the Future

The prospects for the future based on the success of this study are promising. The correlation between nighttime lights DNB data obtained from satellites and various socioeconomic parameters opens up possibilities for estimating and studying other relevant indicators. By establishing the exact mathematical relationship between the correlated socioeconomic parameter and DNB data, further insights can be gained. In the field of education, for example, the literacy rate of an area can be correlated with DNB data to understand the relationship between nighttime lights and educational development. This approach can be extended to other socioeconomic parameters such as poverty rates, income levels, access to healthcare, and infrastructure development. By analyzing the correlation between these parameters and DNB data, valuable information can be obtained to inform policy decisions and targeted interventions.

As technology continues to advance, the image resolution of nighttime lights data is expected to improve. Finer resolution data will provide more detailed and accurate information about urban areas, allowing for better analysis and understanding of socioeconomic patterns and trends[27]. This increased resolution will enable the identification of smaller hubs within urban regions, such as industrial hubs, residential clusters, healthcare centers, and commercial areas. By studying these hubs separately, specific socioeconomic parameters associated with each hub can be addressed, leading to more targeted and effective urban planning and development strategies.

Overall, the success of this study in utilizing nighttime lights data for socioeconomic analysis opens up new avenues for addressing future challenges in urban regions. The potential applications are vast, and the study's findings can be utilized to address a wide range of issues and inform decision-making processes for sustainable and inclusive urban development.

7. Conclusions

In conclusion, this study demonstrates the potential of remote sensing, specifically VIIRS/DNB data, for understanding the dynamics of urban area growth and its correlation with socioeconomic parameters. By analyzing the brightness data derived from night time lights, the study establishes a relationship between urbanization and GDP growth in Delhi NCR. The findings highlight a statistically significant correlation between the growth of urban areas and the increase in GDP in the region. The regression analysis enables the prediction of GDP values based on VIIRS/DNB data, providing a unique method for estimating important socioeconomic parameters like GDP. The study's prediction for the GDP of Delhi NCR in 2023 is 1,02,00,000 million INR. This indicates the continued growth and economic development of the region. However, the study also highlights the potential environmental and ecosystem threats associated with rapid urbanization in high-growth areas.

Overall, this research demonstrates the value of remote sensing data and its application in understanding urban dynamics and socioeconomic trends. It provides insights into the relationship between urbanization and GDP, offering a basis for informed decision-making and urban planning to ensure sustainable and balanced development in the future.

Authors Contribution Statement

Raghvendra Singh: Analysis of RS and GIS, Data collection, Writing – original draft, Writing – review and editing. Varun Narayan Mishra: Supervision. Sudhakar Shukla: Study Conception, Design, Supervision, Shivendra Singh: Writing – review and editing, analysis of RS and GIS, Study Conception and Draft manuscript preparation

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