Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Identification of Urban Growth Patterns in Sri Lanka Using Viirs Night-Time Lights Data

Kajarani E.

kajamuruganrani@gmail.com

Sabaragamuwa University of Sri Lanka https://orcid.org/0009-0004-0474-5517

Nalani H.A.

Sabaragamuwa University of Sri Lanka

Research Article

Keywords: VIIRS Nighttime Light, Urban growth pattern

Posted Date: April 1st, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9250627/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: The authors declare no competing interests.

Abstract

Today, urban growth is a multidimensional spatial and dynamic process that inclines towards increasing the significance of urban planning for developing countries with rapid growth of population and economy. Unplanned urban growth decreases the quality of urban environment. It is vital to study the urban change patterns to help for the decisionmaking process of urban planning. But, in developing countries like Sri Lanka, facing challenges in acquiring information to investigate the urban patterns. Therefore, the use of advanced technologies is indispensable for the identification of urban growth and for sustainable urban planning. Nighttime light data obtained from the Suomi National Polar Orbiting Partnership's Visible Infrared Imaging Radiometer Suite (NPP-VIIRS) sensor provides a new source of information that is advantageous for mapping and monitoring urban growth. Aiming at the knowledge gap in the use of VIIRS Nighttime Light data for urban studies in Sri Lanka, our study examined the capability of using VIIRS NTL data for the urban growth pattern identification. We used the nighttime data derived from the Suomi National Polar-Orbiting Partnership's Visible Infrared Imaging Radiometer Suite (NPP-VIIRS) sensor for the years from 2013 to 2021 to extract the urban extent and Regional Light Index for the spatial-temporal analysis. The results revealed that VIIRS NTL data has high potential in identification of urban growth patterns. Furthermore, we employed the CA-Markov model to predict future urban growth for 2026. The findings of the research will be very useful for the urban planners and policy makers to formulate better policies and strategies for future urban development in Sri Lanka.

1. INTRODUCTION

All over the world, urbanization has become a universal and significant phenomenon in society and economics. Urbanization is a complex socio-economic process that transforms the built environment, converting formerly rural into urban settlements, while also shifting the spatial distribution of a population from rural to urban areas (United Nations, 2018). In the past few decades, urban areas have been expanding drastically in many developing countries. According to the latest World Urbanization Prospects (United Nations, 2018), 55% of the world's population lived in urban areas in 2018 and by 2050, 68% of the world's population is projected to be urban, with almost 90% of the growth happen in Asia and Africa.

As a developing country, Sri Lanka is experiencing rapid urbanization, driven by population growth, rural-to-urban migration, and economic development. As cities expand rapidly, understanding urban growth patterns becomes imperative for sustainable development and effective urban planning. Understanding how cities are expanding and evolving is crucial for policymakers and urban planners to make informed decisions and mitigate the negative impacts of rapid urbanization. By studying urban growth patterns in Sri Lanka, valuable insights can be gained to guide future development strategies and promote sustainable urbanization. However,identifying of the urban growth patterns in Sri Lanka is still a difficult task and on-going research.

Up to present, various attempts have been employed to extract urban extents in the field of geographic information science including field surveys and classification of remote sensing images (Bhatta, 2009; Dadras, 2015; Weerakoon, 2017). However, field surveys are resource-intensive and impractical for large-scale urban studies due to their time and labour demands. Advancements in remote sensing have led to an increased reliance on satellite imagery for urban studies. Traditional methods typically involve classifying medium to high-resolution data such as Landsat satellite images (Subasinghe et al., 2016; Jayasinghe et al., 2021). But, they have several shortcomings such as a huge workload to process a large amount of cloud-free data and addressing issues of spectral and spatial inconsistency across different images. Moreover, their limited temporal resolution constrains their suitability for dynamic analyses at broader scales (Sexton et al., 2013).

To overcome the limitations of traditional land-use and land-cover mapping techniques, night time lights data has emerged as a powerful tool for analysing urban growth patterns. Night time light images measure emitted radiation rather than reflected radiation, which offers certain advantages for distinguishing between developed and non-developed land cover (Sutton, 2003). The DMSP-OLS and SNPP VIIRS are two commonly used instruments for collecting night-time lights data. In other countries around the world, DMSP-OLS night time lights data has been used successfully for urban analysis (Zhou et. el., 2015; Jiang et. el., 2020). For example, Liu et al., (2012) highlights the significance of night time stable light data obtained from the Defense Meteorological Satellite Program's Operational Line-scan System (DMSP-OLS) Night time Lights Time Series dataset, for studying urban expansion in China. Also, DMSP/OLS NTL data have been used in other countries and proved the uniqueness and usefulness of night-time light data for analysing and monitoring urbanization, particularly in areas with limited statistical data (Jiang et. el., (2020). In Sri Lankan context, DMSP-OLS NTL data have been used successfully for urban growth pattern analysis by Yapa and Gunawardena (2022). However, these data have some shortcomings include limited data availability for certain years, blooming effect, pixel saturation, conflation of electricity production with gas flares, signal decay, and systematic shifts in the geospatial position of digital numbers.

Acknowledging the limitations of DMSP-OLS NTL data, the researchers have turned to newer and more advanced sensors like Suomi National Polar-orbiting Partnership (SNPP) Visible Infrared Imaging Radiometer Suite (VIIRS) to overcome these limitations (Shi et. el., 2014; Yu et. el., 2018,). The VIIRS offers significant improvements over the OLS, including higher spatial resolution, wider dynamic range, better quantization, more accurate calibrations, and the availability of spectral bands suitable for discriminating thermal sources of light emissions (Elvidge et al., 2013). Few research works have demonstrated the applicability of VIIRS images for analysing urban growth patterns in other countries in the world. For instance, one study used the night time stable light data from VIIRS for studying the spatial structure of urban agglomerations in China (Zheng et. el., 2021). Unfortunately, no research has yet been developed related to analysing the relationship between VIIRS NTL data and urban growth patterns in Sri Lanka.

So, the research problem is “is VIIRS nighttime light data suitable to analysis the urban growth patterns in Sri Lanka?”. Therefore, to fill the knowledge gap in Sri Lanka, the study aims to analysis the relationship between the VIIRS NTL image data (illumination patterns) and urban growth patterns in Sri Lanka.

2. METHODOLOGY

2.1 Study Area

The study covers the Colombo district which is in the western part of the Sri Lanka (Fig. 1). It has 13 Divisional Secretariat Divisions. Colombo is located at 6.8602^{o}N latitude and 80.0535^{o}E Longitude geographic coordinates and has a total administrative area of approximately 699 km^{2}. It is the commercial capital and most financial district in the Sri Lanka. Colombo District's population was 2,375,000 and urban area population was 2,219,782 in 2015. It has the highest population and population density in Sri Lanka. The population density is 11.4%.

2.2 Data Used

The VIIRS Night time Day/Night Annual Band Composites Version 2.1 imagery was acquired from the NOAA website at http://payneinstitute.mines.edu/eog/. Data was downloaded for the study period of 2013 to 2021. The spatial resolution of the products was 15 arc seconds. The version 4 DMSP-OLS stable nighttime lights annual image composites for the year 2013 was obtained from the NOAA website at http://payneinstitute.mines.edu/eog/. The spatial resolution of the products was 30 arc seconds. The data was used to extract the urban area and compare the result with the VIIRS urban extraction information. Global annual Land cover map of 2013 produced by the European Space Agency (ESA) Climate Change Initiative (CCI) was obtained from ESA CCI land cover website https://www.esa-landcover-cci.org/. The spatial resolution of the data is 300m.

2.3 Data Pre-Processing

For the VIIRS images, the downloaded images were ready to be used in research as they had already been filtered to depict stable light. Therefore, the cloud cover, stray lights, lightning, and lunar illumination are filtered out of the images available for download. The DMSP/OLS and VIIRS NTL data series were accurately projected to the WGS 84 / UTM zone 44N coordinate system and images were resampled to a spatial resolution of 300 meters.

2.4 Extraction of Urban Information

The Optimal Threshold Method (OTM) was employed to extract urban and non-urban areas from the study area. A DN value of 3 was selected as the optimal threshold value for VIIRS data. After that, a classification accuracy assessment was conducted to evaluate the accuracy of the results.

2.5 Spatial-Temporal Changes Analysis

The Region Light Index (RLI) model offers an effective approach to assess nighttime light (NTL) intensity by considering both DN values and regional characteristics (Xu et al., 2016; Yapa & Gunawardena, 2022).

$$RLI = \frac{\varvec{S}_{\varvec{u}} \times \varvec{N}_{\varvec{u}} \times \varvec{a}}{\varvec{S}} + \frac{\varvec{S}_{\varvec{n}} \times \varvec{N}_{\varvec{n}} \times \varvec{a}}{\varvec{S}} \quad \text{..... Eq. (1)}$$

Where, S*u* and S*n* represent the respective areas of urban and non-urban regions within the study area. N*u* and N*n* represent the number of pixels corresponding to each land use and a, b refer to the average DN values of each region. S represents the total area of the study region.

2.6 Prediction

The study applied the CA-Markov model to simulate and predict future urban growth in Colombo. The change analysis was done using Land Change Modeller and the transition matrix was calculated using Markov chain model in IDRISI software concerning variations from 2014 to 2020. Applying the CA Markov chain technique, a projection for 2026 was done.

3. RESULTS ANALYSIS AND DISCUSSION

3.1 Accuracy assessment based on finer-resolution remote sensing data

The accuracy of the extracted urban information was evaluated using finer-resolution remotely sensed data. The evaluation aimed to validate the accuracy and reliability of the extracted urban information by comparing it with higher-resolution datasets (Fig. 3).

The use of finer-resolution remotely sensed data, such as high-resolution satellite imagery or aerial photographs, allowed for a detailed comparison with the extracted urban information. The ESA Land Cover data has a finer spatial resolution (300 m) compared to the NSL data (1 km or 500 m). So, evaluating the results using ESA Land Cover is feasible and widely accepted (Cao et al., 2009; Henderson et al., 2003; Small et al., 2005; Sutton et al., 2006).

The accuracy assessment, conducted through the random selection of urban and non-urban points, demonstrates a high level of accuracy in the urban area extracted using VIIRS NTL data. The overall accuracy for urban area detection is 90.95%, with a kappa coefficient of 0.82 (Table 1).

Table 1
Error matrices and accuracy assessment for urban and non-urban area extracted using VIIRS NTL data.

Classified Data	Reference Data			User's Accuracy
	Urban	Non-urban	Row total	
Urban	87	14	101	86.14%
Non-urban	05	104	109	95.41%
Column total	92	118	210	
Producer's Accuracy	94.57%	88.14%		
Overall Accuracy = 90.95% ; Kappa = 0.82				

A comparative analysis was performed by evaluating the results obtained from the DMSP data (Table 2). The findings from the accuracy assessment indicate an overall accuracy of 87.38% for the DMSP data, with a corresponding kappa coefficient of 0.75. These metrics provide a measure of the agreement between the classified urban areas and the reference data. Comparing the accuracy assessment results between the VIIRS and DMSP data, it is evident that the VIIRS data outperforms the DMSP data in terms of detecting urban areas.

Table 2
Error matrices and accuracy assessment for urban and non-urban area extracted using DMSP NTL data.

Classified Data	Reference Data			User's Accuracy
	Urban	Non-urban	Row total	
Urban	92	25	117	78.63%
Non-urban	1	88	89	98.88%
Column total	93	113	206	
Producer's Accuracy	98.92%	77.87%		
Overall Accuracy = 87.38%; Kappa = 0.75				

3.2 Urban growth pattern identification

The change trend of land use types in Colombo from 2013 to 2021 is the non-urban area is decreasing, and the urban land is increasing noticeably (Fig. 4).

Over the study period from 2013 to 2021, the urban area experienced consistent expansion, increasing from 351.721 sq. km to 401.805 sq. km. This growth signifies the continuous development of urban areas within the district. Concurrently, the non-urban areas witnessed a decline, indicating the conversion

of non-urban land into urban use. The non-urban area decreased from 333.230 sq. km to 283.176 sq. km, suggesting the encroachment of urbanization into previously non-urbanized regions (Table 3).

Table 3
Area Statistics of urban and non-urban extents in Colombo from 2013–2021, Area units; km^2

Year	Urban	Non-urban	RLI
2013	351.72	333.23	57888.14
2014	355.72	329.23	59083.75
2015	363.27	321.71	61406.25
2016	367.72	317.17	62793.70
2017	376.72	308.08	65656.35
2018	378.89	306.09	64196.93
2019	387.04	297.85	69037.61
2020	389.97	295.01	70018.44
2021	401.81	283.18	74050.26

Regional Light Index (RLI) displayed an upward trend (Fig. 5). This intensification of urban brightness and activity indicates the increasing development and population density in urban areas.

According to the results, the expansion of urban extents during 2013–2021 periods shows Edge expansion pattern (Fig. 6). Edge expansion results with the increase in the size of urban areas, as well as the emergence of new patches near or within existing patches.

Furthermore, results were compared with the past studies conducted in Colombo District. In Fig. 8, (a) shows the spatial pattern variation derived from the DMSP/OLS Night time Light data (Yapa and Gunawardena,2022) and (b) represents the built-up areas and other land use types extracted from Landsat satellite images (Antalyn and Weerasinghe, 2020). Both studies also highlighted the edge expansion in urban growth pattern in Colombo District which is same as our analysis.

3.3 Stimulation and Prediction

The dynamics of urban and non-urban areas from 2014 to 2020 shows that urban areas have witnessed a substantial increase and indicate the urbanization and development (Fig. 9).

Notably, urban areas exhibited substantial growth with the significant net increase of 78.49 km^2. Non-urban areas experienced a notable decrease, with the net loss of -78.49 km^2. It shows that most of the non-urban areas transformed into urban areas (Fig. 10).

A matrix of transition probability offers a quantitative understanding of how urban and non-urban extents change over a specific period using Markov chain analysis (Table 4). The probabilities indicate the specific information about the likelihood of class transitions. The Transition Probability Matrix indicates that there is a high probability (0.7861) of non-urban land transitioning into urban land. Conversely, the probability of urban land changing into non-urban land is relatively lower (0.0046).

Table 4
Transition Probability Matrix

Class	Non-urban	Urban
Non-urban	0.7861	0.2139
Urban	0.0046	0.9954

Based on the Transition Probability Matrix, the projection for land use in 2026 was done(Fig. 11). It is expected that there will be a substantial increase in urban land, as non-urban areas are likely to transform into urban areas with a high probability. This suggests that urban expansion will continue to change the landscape in the study area

4. CONCLUSION

The present study aimed to assess the suitability of VIIRS nighttime light (NTL) data for urban studies in Sri Lanka. Specifically, we conducted an analysis of the urban growth pattern in the Colombo District using VIIRS NTL data spanning the period from 2013 to 2021. The findings of our study provide compelling evidence that VIIRS NTL data can effectively be employed for urban extraction and offer an accurate and comprehensive approach to mapping urban growth. By leveraging the spatial distribution of nighttime lights, VIIRS data enables the identification and delineation of urban areas with a high degree of precision. The significant advantage of utilizing VIIRS NTL data is its ability to overcome the limitations associated with traditional methods of urban growth pattern analysis. Unlike conventional techniques, VIIRS NTL data provides a robust and objective source of information. This not only enhances the accuracy of urban mapping but also facilitates rigorous and consistent analysis of urban growth dynamics.

The application of VIIRS NTL data in urban studies can greatly support urban planning, land use management, and policy formulation in Sri Lanka. The accurate and reliable mapping of urban growth patterns enables decision-makers to better understand the spatial extent and intensity of urbanization, facilitating the identification of areas that require targeted interventions for sustainable development.

It is important to acknowledge the limitations of our study. Firstly, the use of threshold methods, although straightforward, is subject to several limitations. The process of dividing sub-regions and determining the optimal threshold is subjective and timeconsuming, potentially introducing bias and inconsistency into the results. Moreover, the challenge of overestimating urban areas persists, particularly in the case of large cities. While there is a strong correlation between nighttime light (NTL)

and urban extent, relying solely on NTL data may not capture the complete urban landscape accurately, leading to potential overestimation. Furthermore, our analysis focused solely on the Colombo District, and further investigations are needed to other regions in Sri Lanka. By acknowledging the above limitations and addressing them through further research, we can enhance the reliability and applicability of VIIRS NTL data for urban studies in Sri Lanka.

In conclusion, our study demonstrates that VIIRS nighttime light data holds immense potential for urban studies in Sri Lanka. The adoption of VIIRS NTL data as a tool for urban extraction offers an accurate and comprehensive method for mapping urban growth, overcoming the limitations of traditional approaches. The findings from the study provide valuable insights for policymakers, planners, and researchers, enabling evidence-based decision-making and supporting sustainable urban development efforts in Sri Lanka.

Declarations

Data Availability:

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

References

1. Bhatta, B. (2009) ‘Analysis of urban growth pattern using remote sensing and GIS: a case study of Kolkata, India’, International Journal of Remote Sensing, 30(18), p.4733-4746.
2. Elvidge, C. D. et al. (2013) ‘Why VIIRS Data Are Superior to DMSP for Mapping Nighttime Lights’, Proceedings of the AsiaPacific Advanced Network, 35, 62.
3. Jayasinghe, P., Raghavan, V. and Yonezawa, G., (2021) ‘Exploration of expansion patterns and prediction of urban growth for Colombo City, Sri Lanka’, Spatial Information Research, pp.1-14.
4. Jiang, S.et al. (2020) ‘Detecting the Dynamics of Urban Growth in Africa Using DMSP/OLS Nighttime Light Data’, Land, 10(1), p.13.
5. Liu, Z. et al. (2012) ‘Extracting the dynamics of urban expansion in China using DMSP-OLS nighttime light data from 1992 to 2008’, Landscape and Urban Planning, 106(1), pp.62-72.
6. Sexton, J.O. et al. (2013). ‘Urban growth of the Washington, DC–Baltimore, MD metropolitan region from 1984 to 2010 by annual, Landsat-based estimates of impervious cover’, Remote Sensing of Environment, 129, pp.42-53.
7. Shi, K. et al. (2014) ‘Evaluation of NPP-VIIRS night-time light composite data for extracting built-up urban areas’, Remote Sensing Letters, 5(4), pp.358-366.
8. Subasinghe, S., Estoque, R.C. and Murayama, Y. (2016) ‘Spatiotemporal analysis of urban growth using GIS and remote sensing: A case study of the Colombo Metropolitan Area, Sri Lanka’, ISPRS international journal of geo-information, 5(11), p.197.

9. United Nations, Department of Economic and Social Affairs, Population Division (2019). World Urbanization Prospects 2018: Highlights (ST/ESA/SER.A/421).
10. Yapa, R.D.W.S. and Gunawardena, W. (2022) 'Examination of the spatio-temporal urban growth patterns using DMSP-OLS night-time lights data: an experiment in urban area, Sri Lanka'.
11. Yu, B. et al. (2018) 'Urban built-up area extraction from log-transformed NPP-VIIRS nighttime light composite data', IEEE Geoscience and Remote Sensing Letters, 15(8), pp.1279-1283.
12. Zheng, W. et al. (2021) 'Analysing the spatial structure of urban growth across the Yangtze River Middle reaches urban agglomeration in China using NPP-VIIRS night-time lights data', GeoJournal, 46 pp.1-18.
13. Zhou, N., Hubacek, K. and Roberts, M. (2015) 'Analysis of spatial patterns of urban growth across South Asia using DMSP-OLS nighttime lights data', Applied Geography, 63, pp.292-303.

Figures

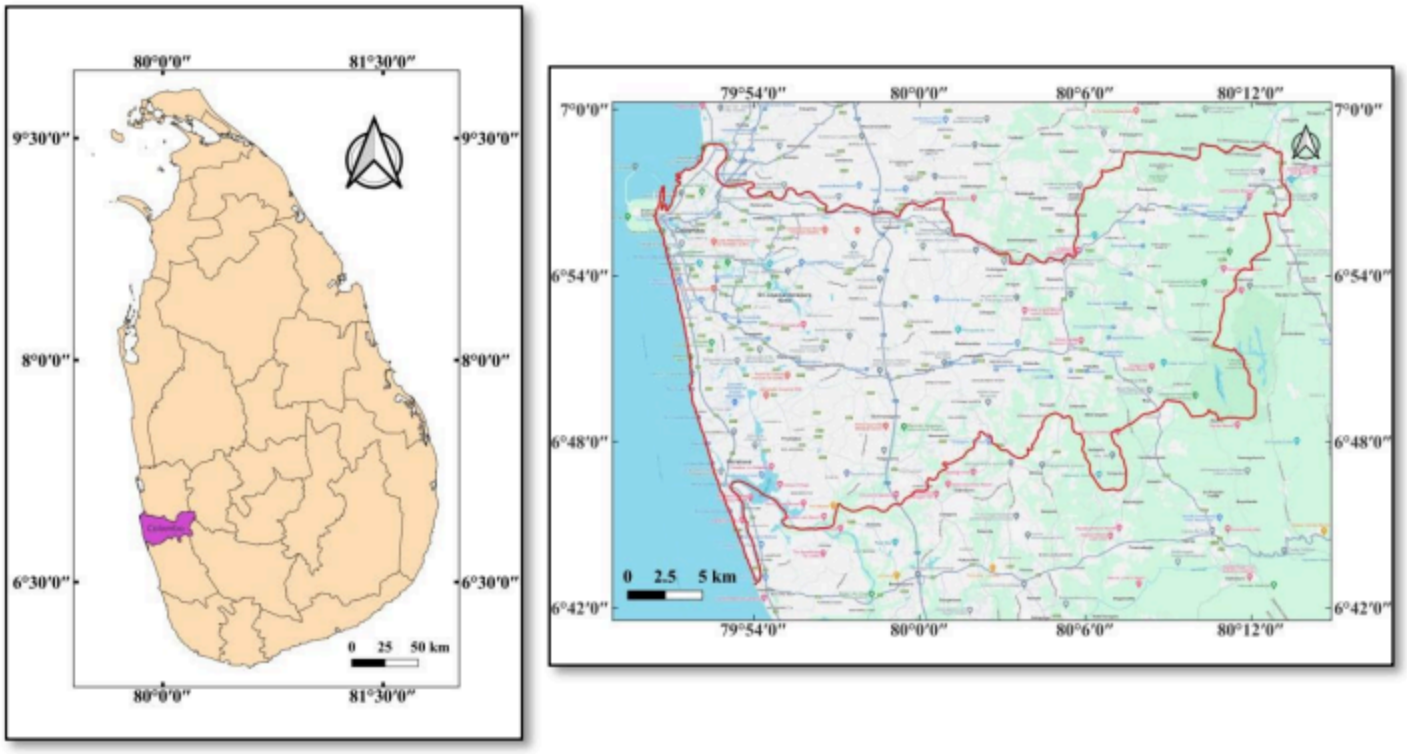


Figure 1

Study Area

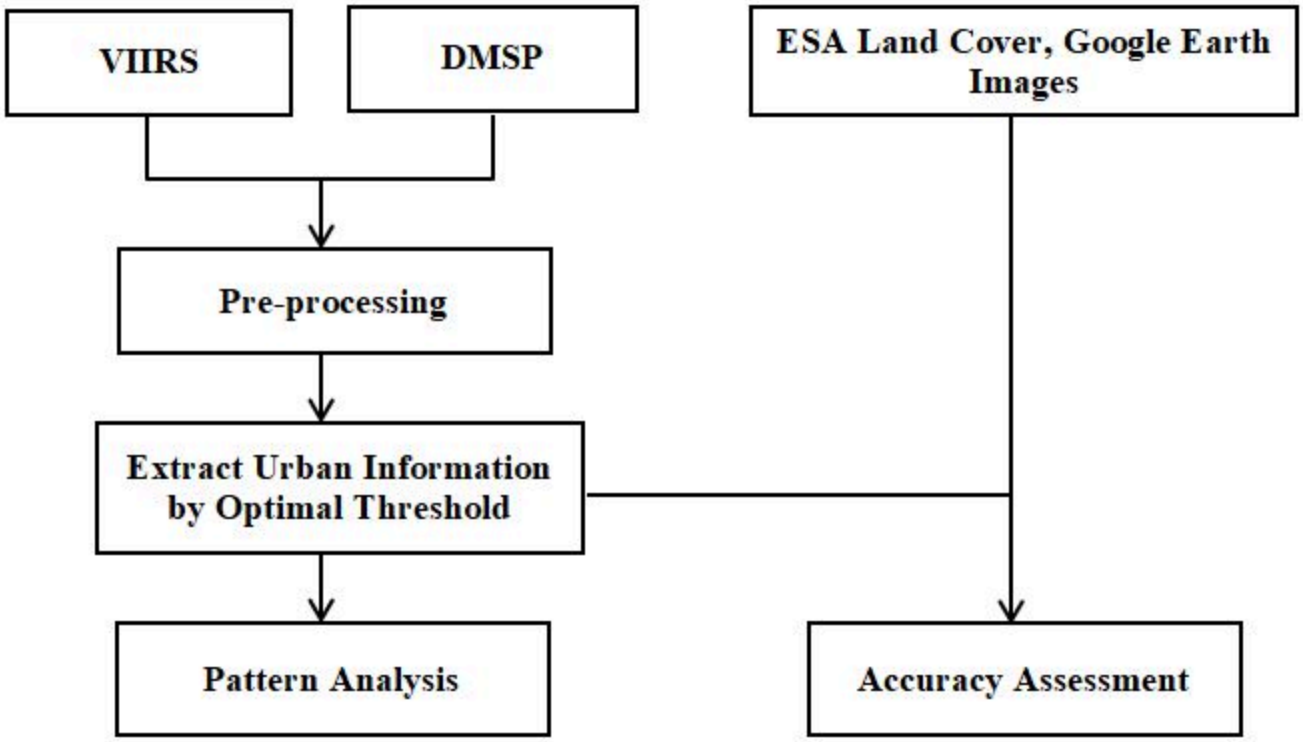


Figure 2

Methodology

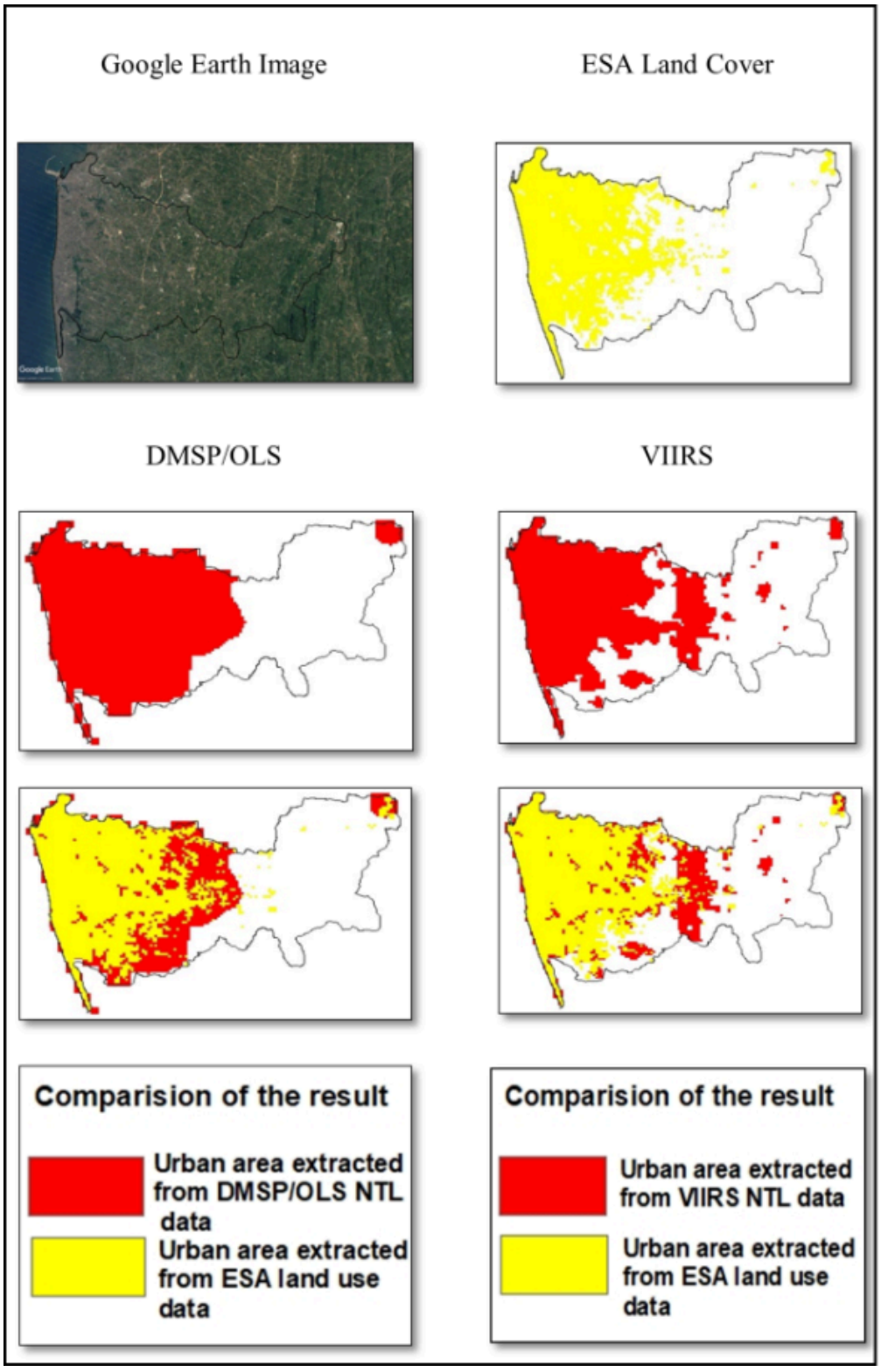


Figure 3

The extracted urban areas in Sri Lanka with ESA data and NTL data, 2013

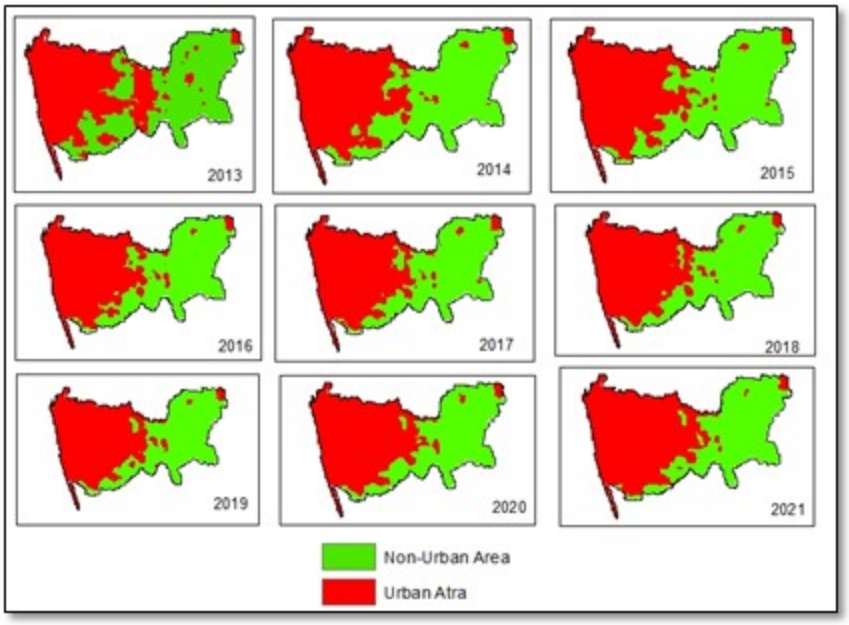


Figure 4

Spatial distributions of land use types in Colombo from 2013-2021

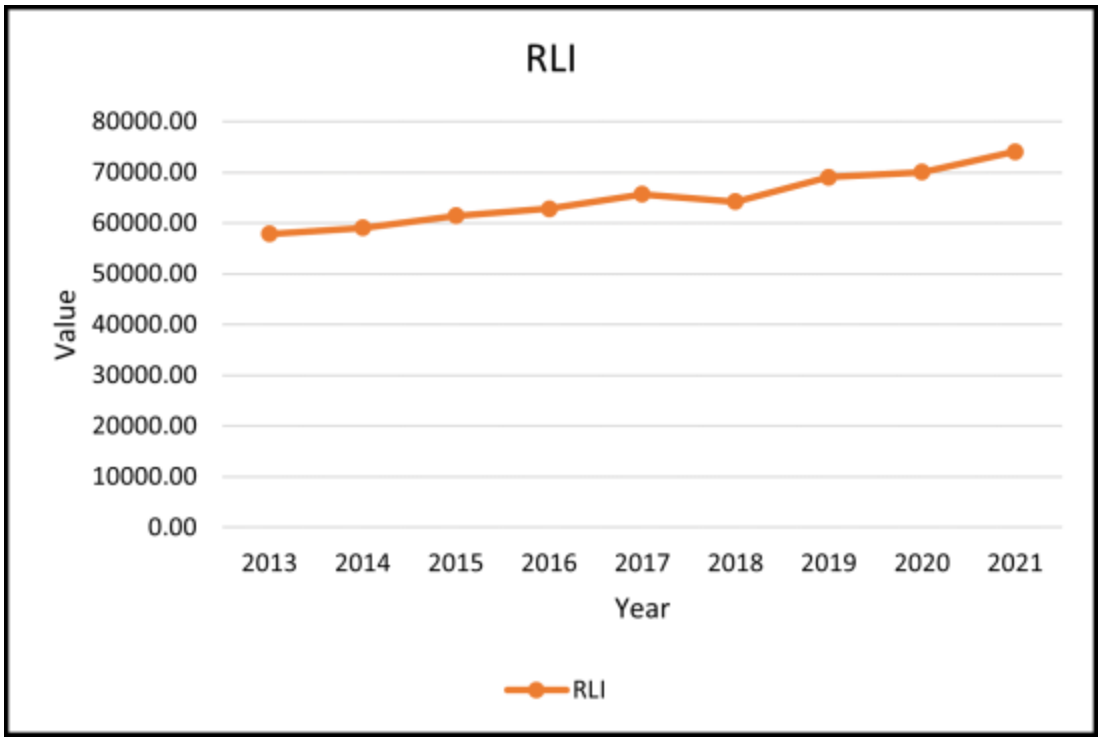


Figure 5

Graph of Regional Light Index

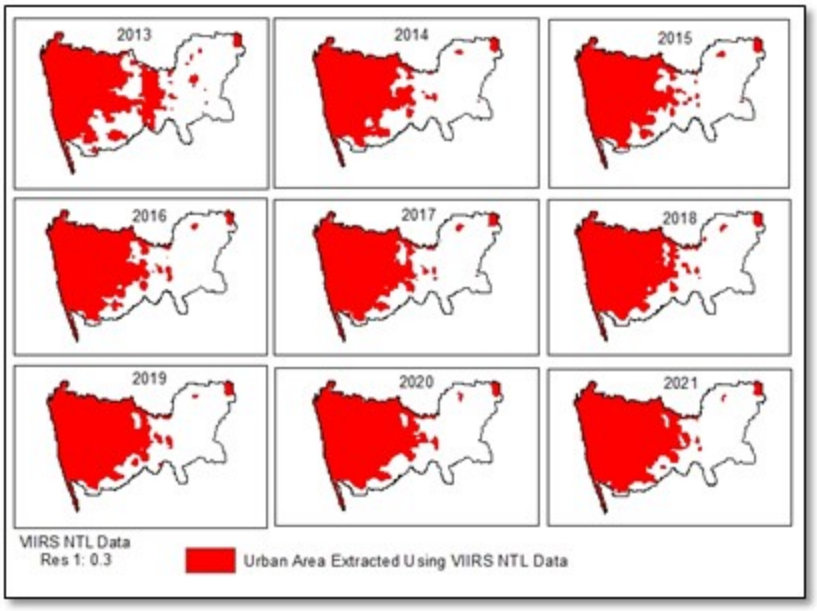


Figure 6

Urban Area Evolution from 2013-2021

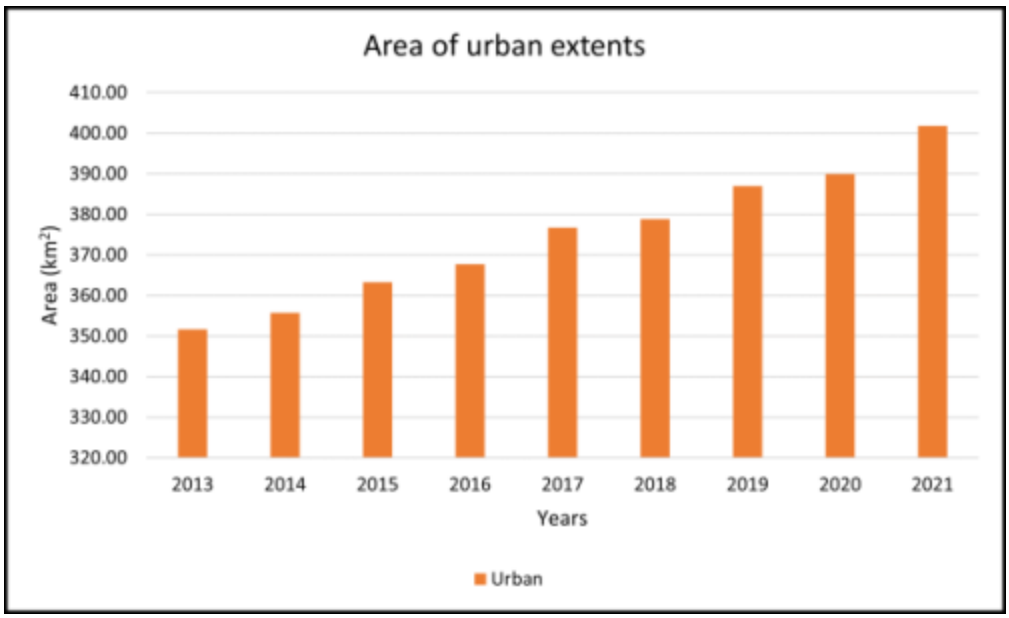


Figure 7

Graph of Urban Area from 2013-2021

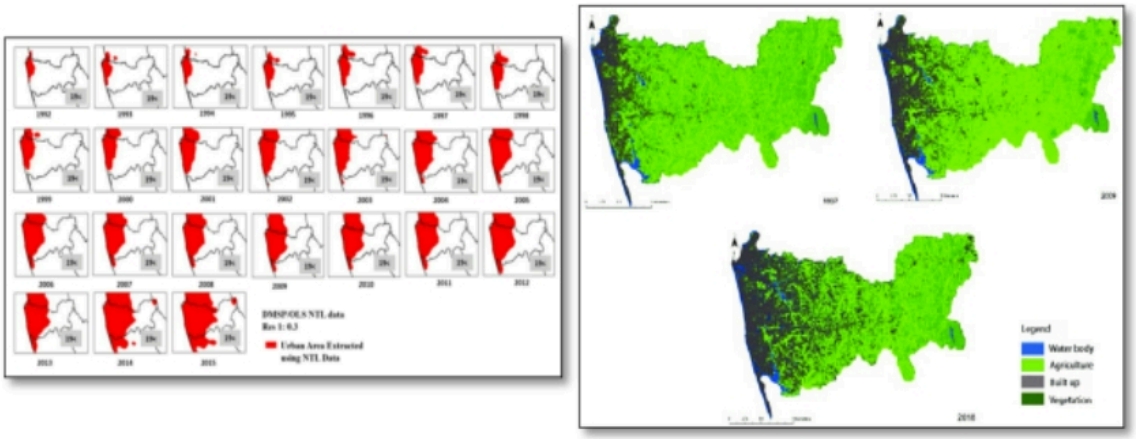


Figure 8

Urban patterns in Colombo District from the Past studies.

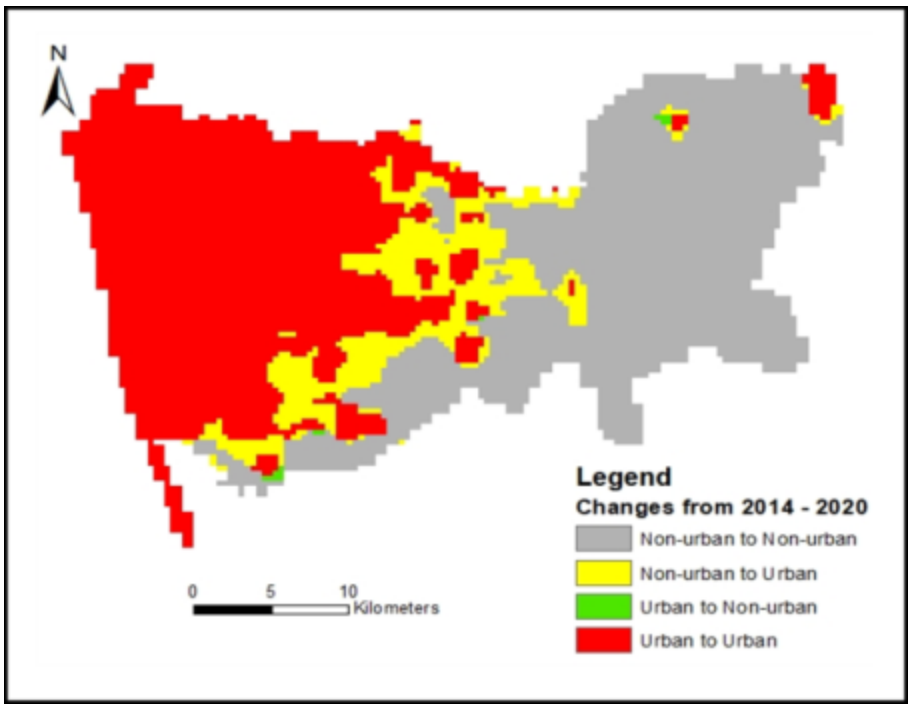


Figure 9

Changes in land use between 2014 and 2020.

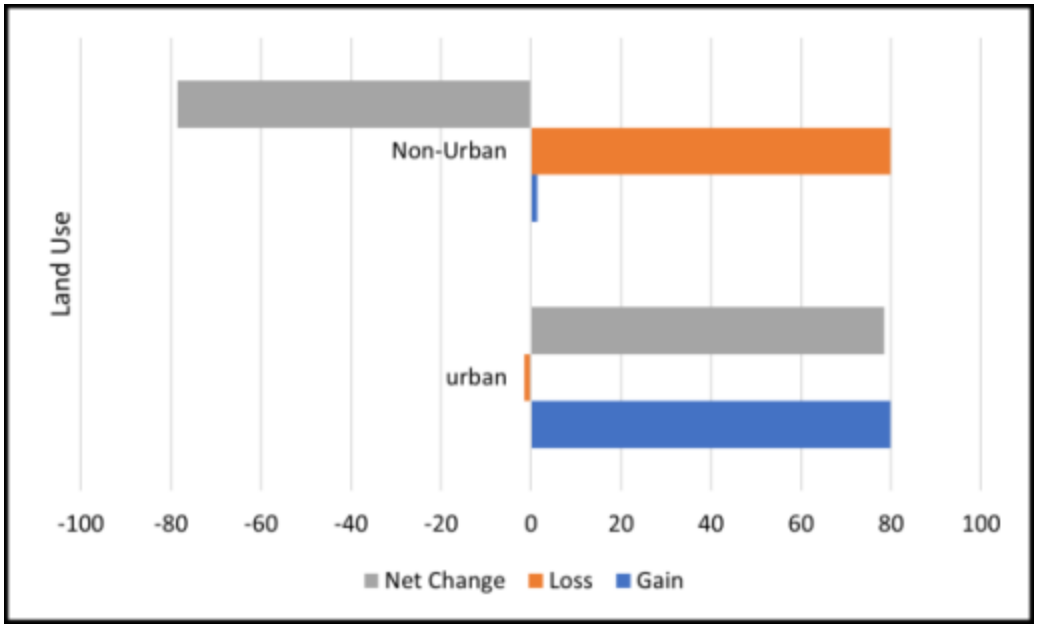


Figure 10

Graph of Net change, gain and loss in km^2.

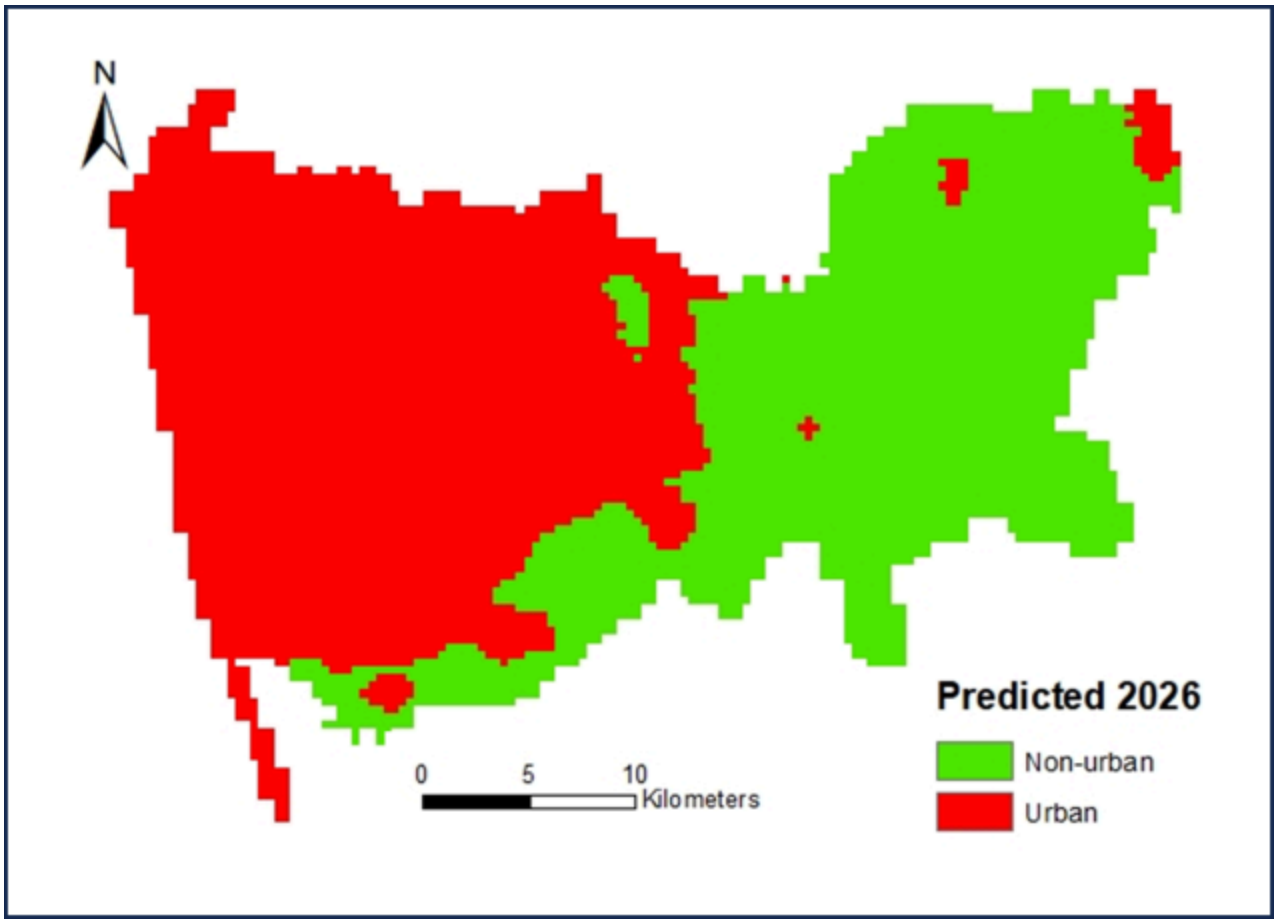


Figure 11

Prediction Map - 2026