EXAMINATION OF THE SPATIO-TEMPORAL URBAN GROWTH PATTERNS USING DMSP- OLS NIGHT-TIME LIGHTS DATA: AN EXPERIMENT IN URBAN AREA, SRI LANKA

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Abstract: Understanding the direction and pattern of the urbanization process is important in urban planning and management. It is important to examine the spatial patterns of urban areas earlier to facilitate the decision-making process in sustainable urban growth. Therefore, urban planners use diverse conventional and non-conventional data portals to investigate the spatial patterns of urban growth. However, in developing countries like Sri Lanka, information about space over time becomes inaccessible. To overcome this shortcoming and to show the usefulness of new technologies, satellite-based Night-time Lights (NTL) data were used in this study to identify the urban development pattern within the existing infrastructure environment. Therefore, the purpose of this study is to show the applicability of "DMSPOLS Night-time Lights" (NTL) data for identifying, analysing urban growth patterns of major towns, as a decision-support process in urban planning in Sri Lanka. The results reveal the urban areas extracted using NTL data in Sri Lanka with a substantial agreement for using NTL data to investigate the spatial patterns of Sri Lanka. This paper explores and guides NTL data processing, and urban area extraction and considers the prospects and challenges relevant to the Sri Lankan context. Thus, there is no doubt about using NTL data for urban analysis in the Sri Lankan context.

Keywords: *Night-Time Light data, Urban Growth Patterns, Decision-Making Process, Spatio-temporal Aspects*

1. Introduction

According to an estimation, by 2050, approximately two-thirds of the human population will be living in urban regions within the world (United Nations. 2014). Concurring to future forecasts, approximately 5 billion individuals will live in urban zones out of around 8.1 billion populaces within the world by 2030. This rapid growth will be highly concentrated in developing countries. Most developing countries have rapid urbanization in cities without adequate planning (Ellis, et.al., 2016). Normally, urban growth patterns are formed based on socioeconomic characters or physical/topographic characters in the area. There are different types of urban development patterns. Monocentric, Polycentric, Linear, and Satellite forms can be seen in Sri Lankan cities (Weerakoon, 2016). That forms and patterns have negative and positive effects. Therefore, identifying urban growth patterns helps the urban planning process driving to ensure sustainability. When considering how planners identify the patterns at present in Sri Lanka, one method is analyzing by comparing the Land Cover (LC) maps with intensity and growth pattern analysis (Jayasinghe, 2020). Other satellite products such as images, OSM (Open Street Map) data are centered on mapping related to the land cover and land use. Night-time lighting outflow signals can be quantitatively interfaced to real-time varieties significant to demography, economy, energy utilization, and urban degree. (Elvidge, et.al. 2015; Ghosh, et.al. 2013).

Consequently, numerous investigative researches have made an effort to look at the affiliation among night-time lights and urban dynamics based on the spatial degree of the cities within the world. Nighttime light images deliver spatially clear observations from synthetic lighting through human settlements at night also without moonlight. (Elvidge, et.al., 2015). Therefore, night-time lights show the exact urban areas, and also, they cover large regions in one image giving an opportunity to view a few cities at once allowing for comparisons. Further, there are historical "nighttime light images" allowing time series analysis of urban growth as well (Naijun, et.al., 2015). This research aims to inspect the affiliation between night-time illumination patterns and urban growth patterns in Sri Lanka. The available images represent the whole country in one image allowing the comparison of urban growth over the time of different town areas in Sri Lanka as good research. Night-time light images for urban growth analysis are successfully used in other countries in the world and research has proved unique qualities of these images in urban growth analysis and future predictions. These images are freely available. Therefore, analysis can be undertaken at

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DOI: https://doi.org/10.31705/FARU.2022.4

a very low cost with high accuracy. It can save money from expensive field analysis techniques. However, unfortunately these kinds of research are not undertaken in Sri Lanka especially for planning purposes. Therefore, through this research, an attempt is taken to show the usefulness of those night-time light data for urban planning.

Research Question is that NTL data have the capability to assess Spatio-temporal urban growth patterns of major towns in Sri Lanka?

As a developing country, Sri Lanka needs to pay close attention to the urban development process. But Information of the space over time becomes inaccessible in Sri Lanka (Subasighe, 2016; Naijun, and Klaus, 2015). Therefore, we have to conclude growth patterns based on the limited data we received. Although it is often known how the city spread in present, it is not known how it gradually evolved in the past. Further, these urban growth modeling happens to individual towns and there is no way to show all the towns at once and analyze their growth variations at once with the available traditional analysis methods. Time series analysis of urban growth shows the correct path of managing and controlling urban growth in urban areas. At the present day-time remote sensing images are used in this analysis (Subasighe, 2016). However, the use of the night-time light illumination patterns along with population data and economic condition of urban areas have resulted from high accuracy in demarcating urban areas over day-time remote sensing data. According to the accuracy assessment, there is a high probability (93%) to identify these transitioning patterns accurately under the global sample, if urbanization occurred. (Qian and Karen, 2013). Thus, the use of night-time light illumination images is useful considering free availability, regional-scale coverage, and accessibility to historical data (Li, et.al., 2017). Defense Meteorological Satellite Program's Operational Line Scan System (DMSP/OLS) provides the time series of NTL data since 1992. In the Sri Lankan context, NTL data is rarely used by the relevant authorities for analyzing urbanization-related activities. To overcome this shortcoming and to show the usefulness of these new technologies, satellite-based Nighttime Lights (NTL) data will be used to identify the urban development pattern and population distribution within the existing infrastructure environment (Mingyu, 2019). Further, there is a knowledge gap and no research has been carried out related to assessing the relationship between an urban growth pattern and NTL data within Sri Lanka. Therefore, this research tries to fill this knowledge gap in Sri Lanka and will pave the path to use night-time data for urban planning-related research.

1.1. THEORETICAL BACKGROUND

'Urban development" can be referred to as a process of converting lands into build environments from residential to cities. It can be defined as a spatial process with complicated effects. For this reason, the spatial process of the region causes changes in the economic status, socially, and political structure of an area. (Dahal, et.al, 2017). 'Urban growth' can be defined as the process of broadening the size of the urban development process. Therefore, it is considered as a spatial, demographical, economic, and social process. The results of this rapid and complex urbanization process are spillover of physical growth to the nearby areas. At that point, urban growth is a continuous process and it keeps changing the spatial structure of urban areas. Some studies regarded urban growth as a static phenomenon. (Weerakoon, 2016). Urban patterns are formed based on the socioeconomic background or physical/topographic attributes in the area. The 'urban growth patterns' are defined as the spreading or conversion of lands into a built environment over time. When data is collected across both time & space, it shows how the same space/location changes from size, density, edge, shape, the distribution of the settlements, and diversity over time. Therefore, the data collection under the above aspects changes over time helps to identify the positive and negative effects through urban dynamics and urban patterns for the decision-making process for urban planners. (Dahal, et.al, 2017). Urban growth theories suppose that the city grew and developed around a single nucleus. But in reality, rapid urban growth causes relatively more complex urban growth patterns than those theories. There are different types of urban development patterns. Monocentric, Polycentric, Linear and edge-expansion forms of urban growth patterns are common in Sri Lankan cities.

Based on the reviews, geographical information system (GIS) techniques and remote sensing tools use to capture the specifics of the urban fabric and discover patterns. Land use and land cover data derived from Remote sensing data such as Landsat images are used to create the urban pattern maps (Seevarethnam, et.al., 2021). Researches face to limitation in availability relevant to Census data from population surveys, Economic details such timely products. Medium resolution Landsat data sources provide the necessary information to some extent relevant to the urban patterns and land-use related studies over spatiotemporal changes. Therefore, urban changes can be mapped by extracting build-up areas from remote sensing data. it's also had some inaccessible with long time series data (Dissanayake, 2020). Google Earth images also help to identify the built environment. But it also has some problems with temporal aspects. Remote sensing data can reduce traditional data acquisition costs but high-resolution satellite data cost can be discouraging the remote sensing data usages. The benefits of remote sensing data, it can concurrently improve the dependability, objectivity, and consistency of information.

DMSP/OLS provides nighttime light images is one of such methods used in the world that related to satellite images for capturing the details of the urban fabric and detect patterns (Akiyama, 2013). Various human activities and land use distribution patterns can be monitored without satellite images in countries like Japan, the United States. Because those countries have different kinds of detailed and updated spatial and temporal datasets and statistics relevant to urban planning. However, it changes when it comes to developing countries because detailed spatial data are not developed adequately and spatial data acquisition is costly for developing countries. (Naijun, and Klaus, 2015). For example, Population data is primary data used to analyze urbanization. It interprets the level of lightning from lightning sources that use in cities, towns, and other areas. DN values (digital numbers) ranging from 0 to 63 interpret the level of lighting. The spatial resolution of these images is 1km 30arc second. In some years, there are two NTL images derived from two satellites. However, census data cannot collect continuously as time-series data. (Mohammed and Shawky, 2021). One study has been undertaken to examine the urban growth pattern of Colombo relevant to the Sri Lankan context, this study referred to a large number of different historical documents to get a conception about previous urban growth patterns time-to-time Colombo. Further, the practical experiences of experts were used in verifying the past urban growth pattern. (Weerakoon, 2016).

1.2. OBJECTIVES

The main objective of this study is to show the applicability of "DMSP-OLS Nighttime Lights" (NTL) data for identifying and analyzing urban growth patterns of major towns or regions in Sri Lanka as a support to the decision-making process in urban planning in Sri Lanka.

2. Materials and Methodology

2.1. DSMP/OLS NIGHT-TIME LIGHT DATASET

"NOAA (National Oceanic and Atmospheric Administration)" provide DMSP/OLS NTL data. (http//ngdc.noaa.gov/eog/dmsp/downloadV4compo sites.html). "Version 4" composite stable light annual product is used in this study. This data set provides cloud-free observations annually using six satellites from F10 to F18 since 1992.

2.2. LAND USE AND SOCIO-ECONOMIC DATASET

Table 1: Land Use and Socio-Economic Data Selected for the Study

Data	Data description	Year
Road network	GIS layers	Covering study period
Land cover	GIS layers/ ESA.NC data	Covering study period
Population data	Census and statistics dept.	Covering study period

2.3. STUDY AREA

In this study, the urbanization pattern at the region level in Sri Lanka was analyzed. Sri Lanka is located in between latitudes 5°55′ and 9°51′ N and longitudes 79°41′ and 81°53′ E. The total area is 65,610 square kilometers. In this study, the selected regions are Colombo, Kandy,Galle,Jaffna.

2.4. METHODS

2.4.1. Data Pre-processing

The data used for this study were in different spatial resolutions. (NTL data – 1km, shapefiles 300 m, Google earth images 1m). Therefore, through resampling methods (Mingyu, 2019) all the data were converted into one spatial resolution. The NTL data series used in this study was correctly projected and resampled into 300 m which is similar to ESA land cover data. the radiometric resolution of images is depicted by the digital number of each pixel and they show the region's average brightness. The stable light data set used in this study may include gas flares. Therefore, the pixels with gas flares were excluded from NTL data using ngdc.noaa.gov gas flare data. (Lowe, 2014). The data set was a subset for Sri Lanka from world image using raster clipping tools before further analysis.

2.4.2. Urban Information Extraction

When selecting the urban areas for this study it is important to consider geographical factors, population, economic factors in urban areas which influence the NTL distribution, for increasing the accuracy of the under. Geographical factors atmospheric parameters, seasonal variations in vegetation relevant to NTL data were considered. (Kyba, 2018). Then the NTL profiles were categorized as urbanized or non-urbanized areas and the sites were interpreted based on the land use/cover, economic activity, and the presence/absence of infrastructure inferred from Google Earth imagery/GIS layers using classification methods. Based on stratified random sampling process Kandy, Jaffna, Colombo, and Galle regions were selected for further studies."Optimal Threshold Method (OTM)" was applied to extract Urban and non-urban information from the selected study areas. It defines pixel values that are verified to have enough accumulation to be classified as a class (as urban area or non-urban area). Those values are closer to reference data are considered as real urban regions (Fangyan, and Shiliang, 2018).

The zonal statistics tools were used to find out relevant data to OTM. According to the literature reviews relevant to the South Asian countries, DN >= 13 is the threshold value to interpret the urban light areas. (Qian and Karen, 2013). The threshold values were extracted following the procedures carried out in similar research undertaken in other similar South Asian countries such as India, Pakistan, Bangladesh (Naijun, and Klaus, 2015). According to the zonal statistics the optimum threshold value, DN >= 19 was relevant to the Sri Lankan context. Therefore DN >=19 was selected as the optimum threshold value for Sri Lankan urban areas. Then consecutive pixels which are in the same range were merged into a single area using an image analysis tool with "bilinear interpolation".

$$a_t = \sum_{i=1}^{\max} (n_i \times s^2) - \sum_{i=1}^{t} (n_i \times s^2) \quad (1)$$

max: maximum pixel value of the NTL image
n_i: number of pixels with values equal to i
s: cell size of the NTL image
at: optimized threshold

After that "Classification accuracy assessment" is the validation method to measure the accuracy of the OTM method which is used to extract urban and non-urban areas from NTL data. NTL data ranges were classified as high densified built-up area, moderate densified built-up area, and low densified built-up area based on DN values. Then the NTL data profiles were compared with Google Earth imagery and GIS land use data, to assess when and where NTL data are able to correctly identify urbanized areas. For that 150 random point samples for each region (Kandy, Galle, Colombo, Jaffna) and overall, 600 samples were selected to measure the accuracy of OTM. Under "Classification accuracy assessment" Cohen's kappa index was calculated which is a multinominal sampling model used to measure the validation quantitatively. Table 2 displays the accuracy assessment results for the whole of Sri Lanka and selected regions. Table 3 interprets the Kappa index values.

Table 2: Summery of Accuracy Assessment with 2012 NTL data

$$\kappa = \frac{p_o - p_e}{1 - p_e} = 1 - \frac{1 - p_o}{1 - p_e}, \quad (2)$$

P_o: observed proportion of agreement

P_e: proportion expect by chance

	High densified	moderate densified	Low densified	Kappa Accuracy
Sri Lanka	72	40	43	0.66
Colombo	40	40	42	0.71
Kandy	39	39	38	0.66
Galle	33	38	42	0.63
Jaffna	29	35	39	0.53

Table 3: Interpretation of kappa index

	poor	Slight	Fair	Moderate	Substantial	Almost perfect
Kappa	<0.0	0.01- 0.2	0.21- 0.4	0.41- 0.6	0.61- 0.8	0.81- 1.0

2.4.3. Spatio-Temporal Changes Analysis

There are some models to evaluate the relationship between urbanization characteristics and nighttime light features. "Region light index (RLI)" is one of the effective methods that can assess NTL data and the regional-wise urbanization characteristics. RLI (Xu, et.al, 2016).

$$\text{RLI} = (S_u \times N_u \times a) / s + (S_m \times N_m \times b) / s + (S_l \times N_l \times c) / s \quad (3)$$

Where Su, Sm, and Sl are the transition areas of high densified built up, moderate densified built up, and Low densified built-up areas. Nu, Nm, and Nl interpret pixels count of each land use; a, b, and c are the average DN values of each land use. S means the total area of the study region. (Xu, et.al, 2016). Under the urban growth pattern recognition, NTL time series data were compared with current case studies of urban morphological patterns in major towns/regions of Sri Lanka without NTL data. (Subasighe, 2016).

3. Research Results

3.1. VALIDATION OF NTL DATA BASED ON FINER-RESOLUTION REMOTE SENSING DATA IN URBAN AREA EXTRACTION

The accuracy of the extracted urban information was assessed based on finer-resolution remotely sensed data. (Ellis and robot, 2016). An urban area is defined as an area where a large number of human activities are concentrated including man-made land cover (Qun and Chunyang, 2014). Under the reviews, most of the studies used the built-up area as an urban area in ancillary data. (Fangyan and Shiliang, 2015). Therefore, in this study, built-up area land cover is used as an urban area for further analysis. Under the "Optimal Threshold Method (OTM)" calculation first, considering DN >= 13.9 value as the threshold value, urban areas were extracted in Sri Lanka (Naijun, et.al., 2015). Then around 300 random sample points within Sri Lanka have been selected under DN (digital numbers) pixel classification categories from NTL data for OTM verification with google Earth data. However, the accuracy assessment determined DN >= 19 (above 19) as the threshold value that applicable to Sri Lanka. Because digital number (DN) class range above 19 identified the urban areas in Sri Lankan boundary more than the DN value >= 13.9 (above 13).

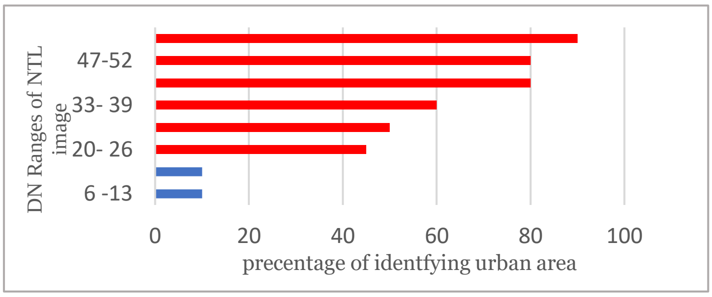

Figure 1: percentage indicate which extent have been identified urban areas under NTL imagery's DN categories.

Figure 1 demonstrates DN ranges of NTL imageries in 2012 as a percentage of urban areas identified. It shows, most urban areas could be identified within the DN value range of over 19. Urban areas were extracted using NTL data in Sri Lanka for all years based on the optimal threshold identified by the year 2012. Figure 1 results revealed that urban boundary extracted using NTL data was compatible with extracted urban areas using ESA data & google earth data within Sri Lanka. It shows an average overall accuracy (OA) of 70% and an average Kappa of 0.66 with NTL data. Therefore, it represents the substantial agreement of the result. Figure 2 displays the measurement of the overall accuracy of selected urban areas for this study.

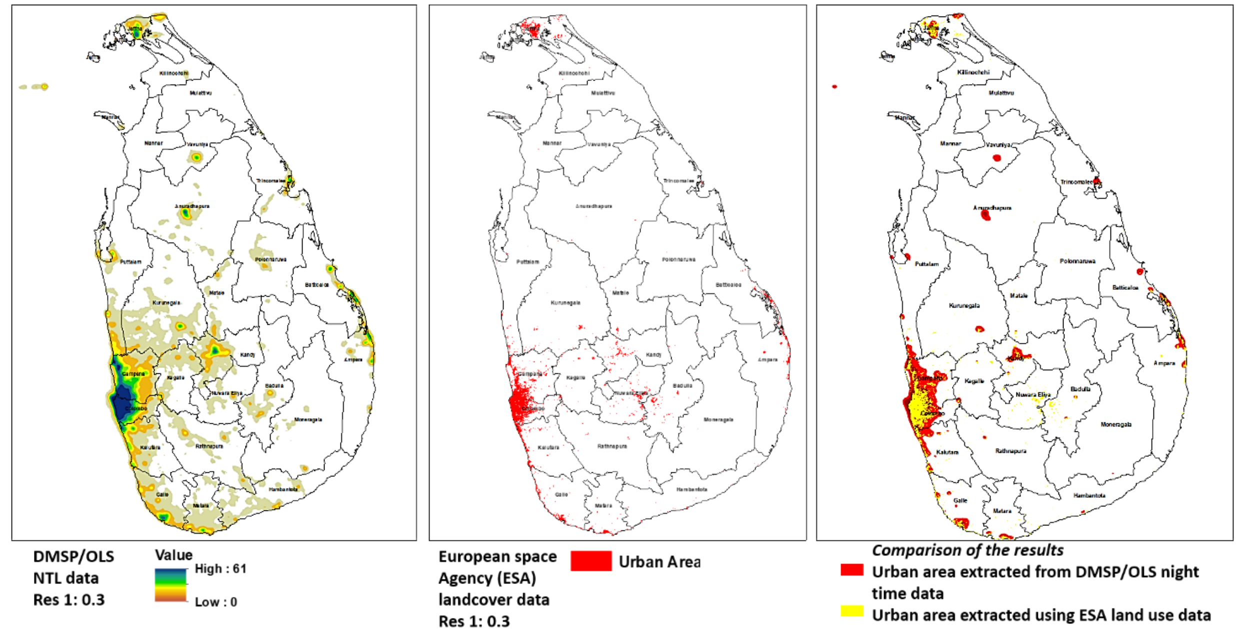

Figure 2: The extracted urban areas in Sri Lanka with ESA data and NTL data, 2012

The accuracy assessment focused mainly in detail on four regions with different levels of urban development with different socio-economic conditions and geographical aspects. They are Kandy, Jaffna, Colombo, and Galle (Figure 2). based on overall 600 random samples used to accuracy assessment, that 150 samples to each region were calculated and extracted. According to the assessment, each region has more than 50% overall accuracy. Colombo, Galle, Kandy interpret substantial average Kappa ((k) > 0.61). However, Jaffna shows a slightly low accuracy level of urban area extraction with moderate average kappa (0.53) than the other three regions. Also, Colombo shows an over-glow effect than the other regions and it shows under figure 3 Colombo region under visual inspection. That causes to overestimate urbanization. Under the literature review, the Overglow effect is a common weakness of NTL data. Open areas are mostly affected and large cities' major transportation lines are also affected by the overglow effect. (Qian and Karen, 2013). In that case, there are some misclassification errors identified within NTL data. Mainly mislabeled low densified built-up or moderate densified built-up areas as highly densified built-up areas because of the saturation effects of NTL data. That is one of the reasons that cause to get substantial kappa accuracy (0.66), not the perfect agreement with NTL data. Vegetation covers are also included in urban areas extracted by NTL data.

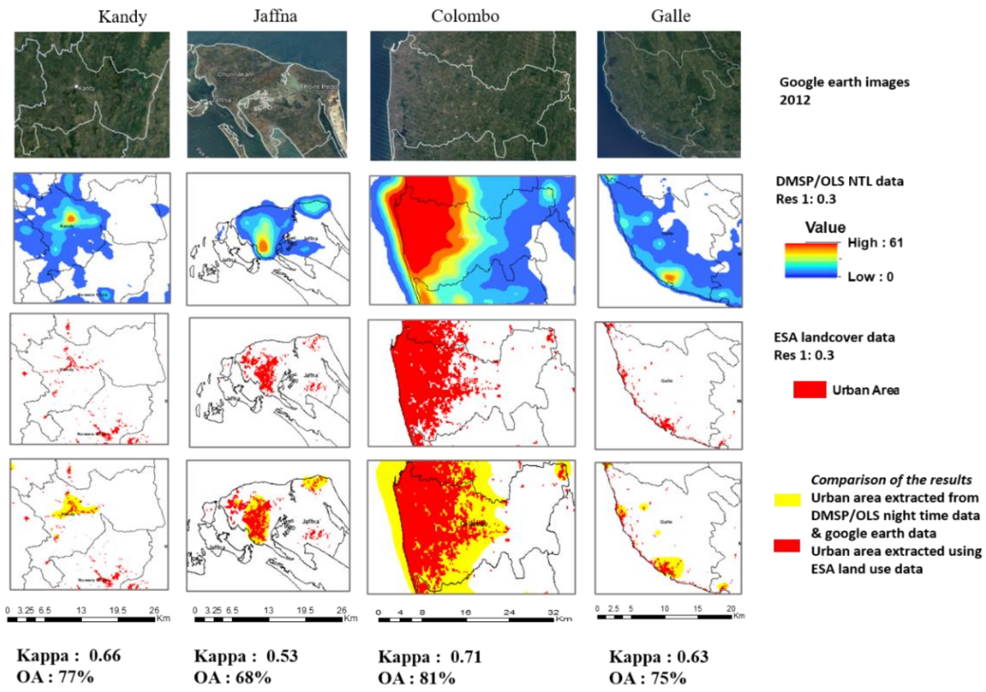

Figure 3: The extracted urban areas in Sri Lanka with ESA data and NTL data, 2012

3.2. URBAN GROWTH PATTERNS IDENTIFICATION USING NTL DATA

3.2.1. Urban Growth Patterns Identification in Kandy

Kandy district is located in the central province of Sri Lanka and Kandy city is an administrative city. The analysis (Figure 4), shows the night light patch expansion in the Kandy region. During the 1990s, it mainly concentrated in the Kandy city area. Gradually within the next decade, the development expanded towards with triangular shape direction. They are Pilimatalawa and Katugastota area. Then 2003 onwards urbanization spreads towards the Pallekale area as well. During 2015 and after that the development has expanded further and Gampola urban area has also merged with the Kandy urbanized area. The development has occurred along with the road network (Figure 5) of the area. Figure 5 shows one of the analysis results in 2015 and the corresponding year Google Earth image as a comparison of analysis results with the real ground.The obtained results through NTL data were compared with the previous studies found in the literature. Figure 6 with table display a summary of past studies carried out in the Kandy urban area. Thus, this comparison is also a kind of accuracy assessment to verify the use and applicability of NTL data in urban area identification and urbanization identification in the Sri Lankan context.

For this research, further “Regional light index (RLI)”. is used with literature reviews to conclude the accuracy of the result obtained from NTL data. Table 4 shows the results of RLI for the Kandy district from 1992 to 2015. Researchers It assesses NTL intensity from DN values of NTL data, to measure urban growth statistically with high accuracy.(Xu and Wang, (2016). Urbanization is one of the complex phenomena that involve spatial dynamic aspects such as land cover, economy, and demography. This section discusses the use of night-time lights, for interpret changing speed of urban areas.

Kandy district has approximately 1922.8 km ^{2} total land area. According to table 4, after 2007, the Highly built-up area has highly increased. Because it increased from 97 km ^{2} to 211 km ^{2} area. However, the growth has become slower after 2007 compared to before 2007 because RLI was decreased from 1513 to 1024. From 1997 to 2002 RLI is increased up to 1028 to 1450 and it interprets steady growth. The first stage (1992 -1997) RLI is 1028 and in fifth stage (2012 – 2015) it shows 1024 value. However, in second and third stages RLI reflect the steady growth and after 2007, it has reduced in Kandy. The low densified built-up area was decreased throughout the study period and most of the low densified BUA has converted to medium BUA. Finally, the result concludes during the period from 2012 to 2015, approximately 11% of area changed as urbanizing area from total land area of Kandy. RLI as well interprets the NTL data growth from time to time.

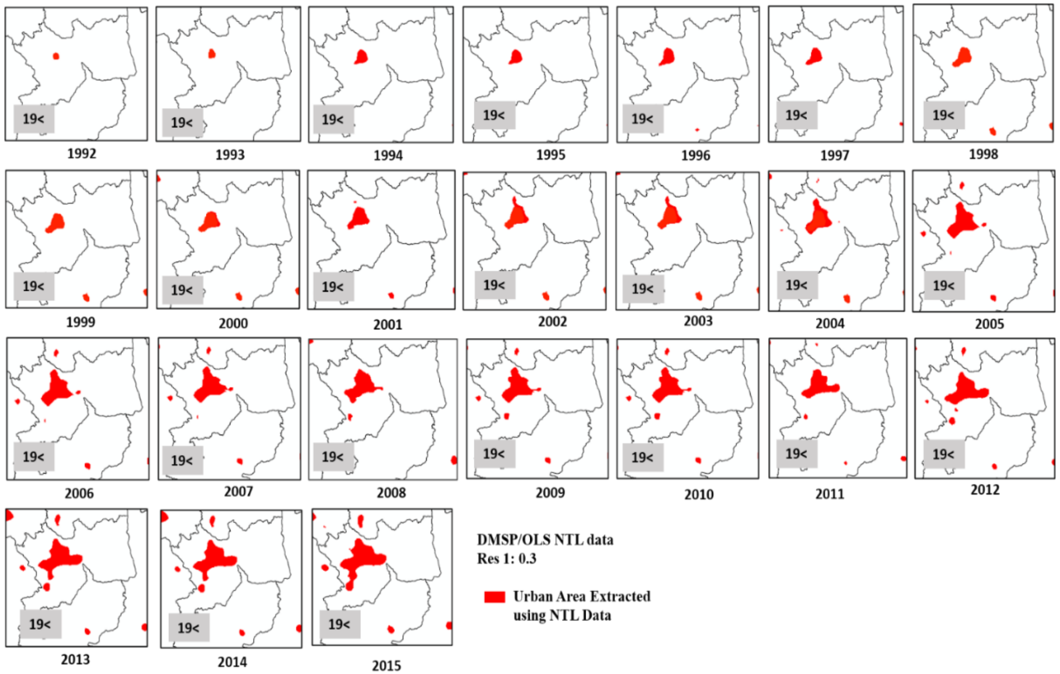

Figure 4: Kandy Urban Area Evolution from NTL data from 1992 – 2015

References	Data source	Spatial pattern
I. (Dissanayake, 2020).	Landsat-5 & Landsat-8 data, google earth imagery	Linear development pattern
II. (Masakorala, 2015)	Satellite imageries and census data	Urban expansion is occurring in three directions based on the main roads.
III. Ranagalage and Murayama, (2019).	Landsat-5 & Landsat-8 data	Linear development pattern

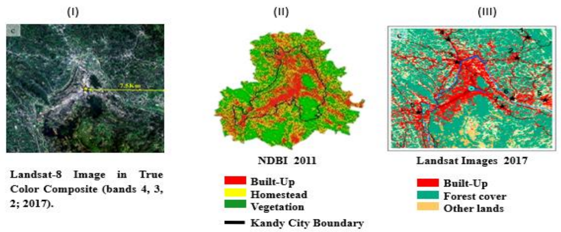

Figure 6: Spatial pattern from past Studies (Table 4) in Kandy Urban Area using maps

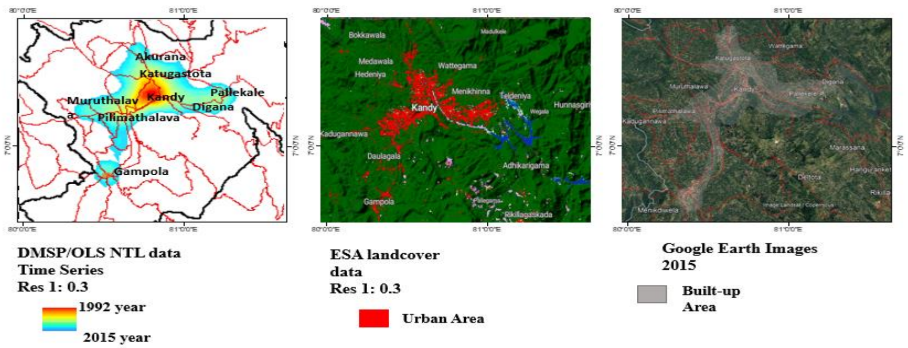

Figure 5: Growing Trend with Transportation Lines, Kandy

Table 4: Area statistics of RLI in Kandy region, Sri Lanka, Area units km^2

Time Period	High densified BUA (DN 27 to 61)	Medium densified BUA (DN 19 to 27)	Low densified BUA (DN < 19)	Region Light Index (RLI)
1992 - 1997	97.2	132.6	1406.6	1028
1997 - 2002	18.1	86.8	1400.5	1450
2002 - 2007	23.3	229.4	1393.8	1513
2007 - 2012	144.2	236.0	1339.0	1271
2012 - 2015	211.9	451.9	1002.3	1024

3.2.2. Urban Growth Patterns Identification in Colombo

Colombo district plays a major role economically and admiratively in Sri Lanka. Since ancient times, Colombo acts as the main economic hub of Sri Lanka. With the open economy, Colombo district develops extraordinary attracting huge population to the district as well. Now, Therefore, it has experienced rapid urban growth. A similar analysis was carried out in the Colombo region and the results are displayed in figure 7.

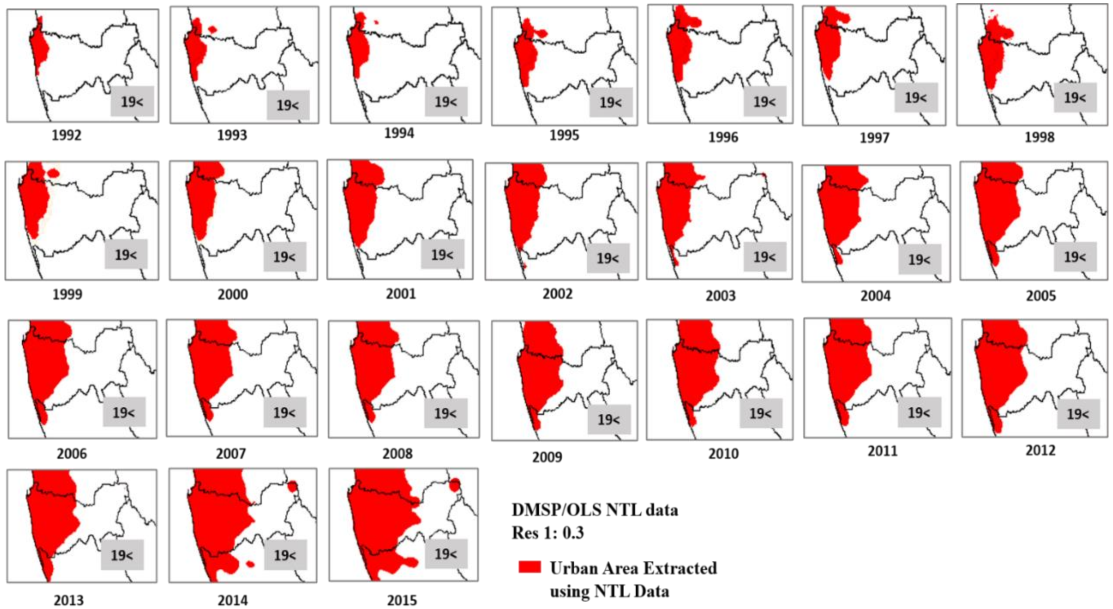

Figure 7: Colombo Urban Area Evolution from NTL data from 1992 – 2015

References	Data source	Spatial pattern
I. (Pavithra, 2020).	Landsat 5 TM & Landsat 8 OLI	edge expansion
II. (Subasighe, 2016)	Landsat 5 TM and historical documentary data	Infill urban development pattern.
III. (Murayama, et.al., 2021).	Descriptive data and GIS data	Edge expansion and outlying growth

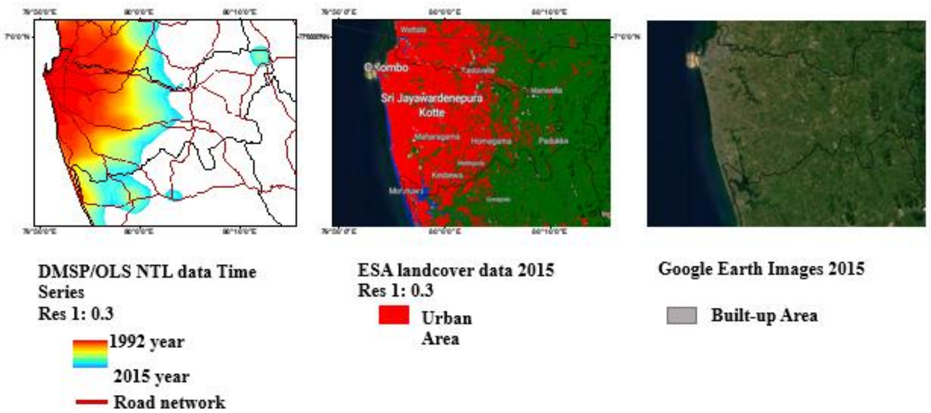

Figure 8: Growing Trend with Transportation Lines, Colombo

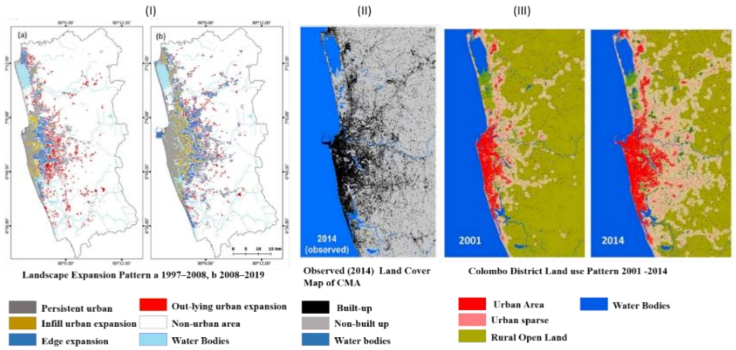

Figure 9: Spatial pattern from past Studies in Colombo Urban Area using maps

According to the results obtained from NTL data during 1992 built-up areas were mainly concentrated around Colombo port and suburb area and during the next three decades, the urbanization has taken place rapidly in the outer areas from Colombo city. Figure 8, shows a comparison of NTL results with Google Earth images and ESA data for the 2015 year. However, the Colombo region has some issues with overestimated built-up area compared to the Kandy region analysis. However, the growth pattern shows an edge expansion growth in the Colombo region. Edge expansion refers to that built-up area that grows to outward from the fringe of exiting urban patches (Murayama, et.al., 2021).

The results obtained through NTL data analysis were compared with the past studies carried out in the Colombo district. Figure 9 displays the figures copied from past studies and Table displays a summary of such past studies. The past studies are also identified Colombo urban growth shows an edge expansion which is the same interpretation through the NTL data analysis.

Colombo district has approximately 679.62 km ^{2} total land area. According to the RLI analysis (Table 5), during the first stage before 1997 built-up area has increased largely than the second stage (after 1997 to 2002). Although there was some decline in the second stage, it is clear that urbanization has spread extensively after 2002. Because after 2002 the RLI has increased from 598 to 2682 and it interprets steady growth. Built-up areas have increased from 253.4 km^2 to 940.9 km^2. The low densified built-up area was decreased throughout the study period. Therefor most of the low densified BUA were converted to medium BUA and medium BUA were transitioned to highly built-up areas. However, we mentioned in previous stage the Colombo region has some over-glow issues with overestimated built-up area compared to the Kandy region analysis. It interprets those total areas (Table 5) were developed as highly BUA between 2012 to 2015 exceeds from the total land area of Colombo district.

Table 5: Area statistics of RLI in Colombo region, Sri Lanka, Area units; km^2

Time Period	High densified BUA (DN 27 to 61)	Medium densified BUA (DN 19 to 27)	Low densified BUA (DN < 19)	Region Light Index (RLI)
1992 - 1997	253.4	160.3	250.1	544
1997 - 2002	160.3	219.6	200.4	446
2002 - 2007	250.1	160.3	199.5	598
2007 - 2012	446.0	101.0	132.6	994
2012 - 2015	940.9	145.6	60.7	2682

4. Conclusion

This study is carried out with the main objective of showing the applicability of "DMSP-OLS Nighttime Lights" (NTL) data for identifying and analyzing urban growth patterns of major towns in Sri Lanka as a support to the decision-making process in urban planning in Sri Lanka. According to the literature review shows as a developing country Sri Lanka, the threshold DN value selected for urban area identification in similar countries was DN >= 13, and also under the threshold calculation DN >= 13.9 for urban area identification. However, this study shows that for the Sri Lankan context it should be DN >= 19 under the accuracy assessment. Thus, this study gives a correct threshold DN value for the Sri Lankan context which will be beneficial for other researchers who are going to use NTL data for different urban study purposes. Although the research was carried out for four regions, the detailed analysis was carried out only for two regions, Colombo and Kandy due to time limitations and the computer issues in analyzing high storage NTL data. Every detailed analysis was tailed with an accurate assessment and a comparison with past literature. NTL data time series provide continuous time series year by year. (1992 -2015).

The Study shows that Kandy is having a linear urban growth pattern towards three directions. Colombo region has coastal to inland urban growth patterns with edge expansion & infill development patterns. The accuracy of the assessment shows NTL data can be successfully used to demarcate Spatio-temporal patterns of urban areas in Sri Lanka and overall NTL data accuracy (OA) was 70% and the average Kappa was 0.66 for the whole country, All regions have a Kappa average greater than 0.5 and overall accuracy greater than 50% which is considered as acceptable accuracy. Thus, the main objective of this study could be successfully achieved with these outputs. Further, NTL data are freely available and all the urban areas can be analyzed at once since NTL data has a regional coverage. Thus, it will save cost and time in analyzing urban areas. Further, a comparison of Spatio-temporal variations of different urban areas at the same time is possible with NTL data since it shows all the urban areas in one image. Although the spatial resolution is low (1km) questioning the accuracy of the output, the study shows that the results are high accuracy with 300m resolution using the resampling method. When considering the prospects and challenges of using NTL data for growth pattern modeling, pre-data processing is a somewhat challenging task with GIS technology and computer capacity. There are some limitations in harmonizing the different pixel sizes of different data sets and NTL data. Further, luminosity in Colombo created a significantly high error percentage relative to the other regions. Therefore, it can lead to overestimating the built-up area and it was proved by RLI analysis. The major prospect is NTL data provide large time-series data year by year and they are freely available. It provide large spatial coverage at once. Finally, the overall study provides the quantitatively positive result for accepting NTL data as an effective data category that can be used to identify the Spatio-Temporal growth patterns in the Sri Lankan context. This study was only focused on the regional level due to time limitations and other ancillary data deficiency of individual cities. If required data and other computer facilities are available, the use of NTL data for urban planning is of greater importance to urban planners and policymakers. Thus, this study suggests thinking about the use of NTL data for urban planning-related studies in the future.

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