Is eThekwini metropolitan municipality (EMM) experiencing light pollution?: A remote sensing analysis of nighttime data of EMM, South Africa

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Abstract
Nighttime light remote (NTL) sensing has improved the approaches taken in studying natural and social sciences. NTLs on the Earth surface can be utilised to study huma-related studies such as urbanisation, population, and light pollution. In most cases, NTL application studies are common in fast developing and developed countries such as China and United State of America while African countries are still left behind in taking part in these studies. The study aimed at assessing the effectiveness of NTL data and the extent of light pollution in urban areas of South Africa. This study explores the use of NTL data in studying light pollution in eThekwini Metropolitan Municipality, South Africa. The study quantified and assessed light pollution and its sources in the Municipality using spatial analyst tools such as reclassification and supervised images classification (Maximum likelihood) algorithm. The classes of light pollution were classified ranging from very low to very high light pollution. With land use land cover (LULC) classes representing main sources of light pollution. The study discovered that light pollution is mainly found in and around the city centre of the municipality where main economic and human activities take place. This is where mainly the built-up and commercial LULC classes were observed to be located. The correlation analysis between light pollution and LULC classes revealed strong correlation between high and very high light pollution classes and these LULC classes. These are the areas making use of artificial light at night leading to light pollution in the Municipality.

Keywords Nighttime imagery · Light pollution · VIIRS/DNB · Urban areas · Development

1 Introduction
As different parts of the world progress at varied socioecono-

mical levels so have the nighttime light (NTL) data. NTL data has become an efficient means to map economic development activities [1]. NTLs are found almost all over the

world, and they serve several purposes. Such as to light up dark areas needed for specific activities at night, such as the location of transportation routes, lighting up residential and commercial areas, or just merely decorating the areas. NTL data is very effective in doing studies that pertain the social and economic activities. This makes it a good proxy to study urbanization, development, energy consumption, and population growth. NTL remote sensing has been receiving great attention in different international countries such as China, the United States of America, the United Kingdom, and Brazil are countries mostly publishing on the use of NTL [2–5].

Presence of artificial light at night has both the positive and the negative sides. It is effective for human practices for the development of the area, but it harms the environment, human body systems and animals. These negative effects mainly result from the occurrence of light pollution. NTL data is an effective approach to study light pollution and its extent [6]. According to a study done by Harris
and Mclean in 2018, 21% of the world’s population lives in areas affected by light pollution. Another study done by Prastyo and Herdiwijaya [2] analysed light pollution in two different areas of Indonesia using the Visible Infrared Imaging Radiometer Suite Day/Night Band (VIIRS DNB) data. Their study discovered that most light pollution increases are seen in less mountainous and urban areas and are still developing those classified as rural areas [2].

NTL studies and light pollution in South Africa and Africa at large are very much unfamiliar [7, 8]. Africa has been considered the least light-polluted continent across the world, according to a study done by Falchi et al. [9], where they presented the world atlas of light-polluted areas around the world. Still, this is bound to change because many African countries are developing electricity provision infrastructure. This means a growth in the NTLs will be experienced. Nevertheless, NTL data is not being put to good use as it should be [10]. Coetzee [7] proposed that more light pollution studies be done in Africa for the above reasons. One study was done by Ogoro, Ernest, and Chukwudi [11] in Nigeria to study the trend of light pollution spatially used only a qualitative method of data collection and analysis such as questionnaires and interviews. There was no involvement of the NTL satellite imagery in their study.

According to Elvidge et al. [12], NTLs are a part of remote sensing that is obtained by observing the existence of artificial lights on the earth’s surface. NTL remote sensing has been growing over time and becoming a focal point for many social and natural scientists [13]. NTL data has a different way from day-time data of tapping into specific human activities associated with the use of artificial light at night [1]. The Defence Meteorological Satellite Program’s Operational Line-scan System (DMSP-OLS), and the Suomi National Polar Partnership (NPP) Visible Infrared Imaging Radiometer Suite (VIIRS) are NTL sources that make NTL data freely available. The DMSP-OLS NTL data is not calibrated, has saturation problems which make it overestimate the lit areas [13]. Both the DMSP-OLS and the Suomi NPP VIIRS DNB are capable of detecting low light imaging data, but the VIIRS DNB data is more improved than the DMSP as it has a better spatial resolution, it is calibrated on board [14], and its spectral bands are single capable of differentiating between light emissions for thermal sources and electric sources [12]. VIIRS DNB NTL data has been therefore the most preferred data source to be employed in NTL application research [15]. NTL data is continuously growing over the years with satellite sensors that provide better quality data and new methodologies to be explored [16]. Many countries have been using this development to their advantage, but African has not. There is still a lack of NTL data studies in African countries as they are not part of the most activities countries [17].

Based on the above background, several studies have been observed in studying different NTL related applications in different countries. Study reviews have proven there is a lack and gap to be explored by African countries looking onto NTL data usage in this region. This study therefore aims to assess the effectiveness of NTL data in studying light pollution in South African urban areas through the use of advanced remote sensing techniques with eThekwini Metropolitan Municipality (EMM) as a study area. The two main objectives include identifying and quantifying light pollution in eThekwini Metropolitan Municipality (EMM) and identifying the causes or sources of light pollution. This study adds to few studies of NTL remote sensing in South Africa.

2 Methodology

2.1 Study area

This research investigated the area of EMM. This metropolitan municipality is one of the 11 districts municipalities found in the KwaZulu Natal (KZN) province in South Africa. It is located southeast of the KZN province, which is the eastern part of South Africa, and it covers about 2256km². The study area map shown in Fig. 1.

According to the Municipalities of South Africa website [18], EMM falls under Category A of the municipalities, which means it is very developed and its economic status is doing very well. This municipality houses the third-largest city in South Africa, Durban. EMM has a population of about 3,702,231, as stipulated in the 2018 KZN Citizen Satisfaction Survey Report. The estimated population growth rate is approximately 1.2% per year. The Community Survey that was done in 2016 to put together a profile for the municipality showed that there are about 1,257,765 households in the municipality, which grew with more than 169,052 households than those that existed in 2011 [19]. The economic profile of the municipality is compounded by different sectors that contribute differently to the Gross Domestic Product (GDP), with tourism contributing about 8%, finance services contributing 21%, manufacturing contributing 19%, trading contributing 17%, transport 14%, and construction with 5%.

Major land uses found at the EMM urban and rural settlements have commercial and transport infrastructure and agriculture. About 32% of the area is urban, with residential, commercial, and industrial areas being the mainland uses [18]. In EMM, the summers are warm and wet, and the winters are long, mildly warm, and not wet nor dry. The temperature around the year ranges between 13 and 27 °C. It is
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rarely below or above these temperatures [16]. This makes it favourable even for touring purposes.

2.2 Nighttime light data

NTL images were retrieved from the National Geophysical Data Centre (NGDC) in partnership with the National Oceanic and Atmospheric Administration (NOAA). The data is collected by the Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP-VIIRS) [20]. VIIRS dataset was chosen to be used in this study because it is better than the other common NTL data source, the Defence Meteorological Satellite Program Operational Line-scan System (DMSP/OLS) (Elvidge et al. 2013). The VIIRS DNB is used because it is the one that can capture the NTL data effectively [12]. The VIIRS DNB has a radiometric resolution of up to 14 bits and can detect the dimmest light at night.

The VIIRS DNB NTL imagery was downloaded from the NOAA website http://payneinstitute.mines.edu/eog/. The data was downloaded for the study period of 2012 to 2018, in the interval of 2 years. The VIIRS satellite sensor for NTL data was launched in 2012. When data collection was done, data availability was up until May 2020, which prompted the research period mentioned [21].

The data was downloaded for each season of the year to improve the study’s time series and improve the variation analysis when the time comes. The four seasons were used each year because, in South Africa, we have uneven energy supplies depending on the season with a decrease or cut-off, especially when in autumn or winter. It meant that each year had four NTL images. These images were used to identify and quantify the light pollution in the EMM, quantifying the intensity according to different classes of light pollution. These classes of light pollution will be shown in Table 3.

2.3 Image processing

To determine the sources of light pollution, the Landsat daytime images were used. These images were downloaded from the USGS Earth Explorer website, where they are available for free. The years used to download these images were the years 2012–2018. One image for each year was downloaded. The summer/spring season was used to download when retrieving the Landsat images because this is mostly later in the year, and the changes that may have taken place are already captured in the images. Table 1 shows the metadata for the Landsat images used in the study.

The supporting data used in the study include the shapefile of the study area used to mask the complete frame of the images into the required study area. The shapefile was downloaded from the municipal demarcation board of South Africa website.

2.3.1 Pre-processing

For the NTL images, the downloaded images were ready to be used in research as they had already been filtered to

Fig. 1 Study area
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recreational areas, vegetation cover, and transportation routes. These classes were adapted from the Anderson classification system [22].

The commercial areas are areas where commercial activities (activities that generate economy in the area) occur. These areas can include shopping centres (retail businesses), services trading areas. The built-up area is made up of residential areas are areas where people reside. These can be their owned homes, rented apartments (flats) or townhouses, industrial areas, and different institutions. Recreational areas are entertainment areas, mostly outdoor entertainment such as stadiums, parks, beaches, etc. Vegetation-covered areas are areas where agricultural activities take place, such as farms, forestry, where there are also just open fields covered by different vegetation, etc. The transportations routes are the roads, railway lines, airports, harbours (harbours mainly involve water as a mode of transport, which explain why water was classified as transportation in the maps of light sources (LULC Maps) to follow [22, 23]. Further description of these LULC classes can be seen in Table 2.

### Table 1 Landsat characteristics

| Year | Landsat Spacecraft ID | LandsatScene Identifier | Date     | TOAor Surface Reflectance | Projection | UTM Zone |
|------|-----------------------|-------------------------|----------|---------------------------|------------|----------|
| 2012 | Landsat 7             | LE71680812012053A       | 2012/02/2| Visible (Bands 1–5,7)     | UTM        | 36       |
|      |                       | SN00                    | 2012/02/2| Visible (Bands 1–5,7)     | UTM        | 36       |
| 2014 | Landsat 8             | LC81680812014258L       | 2014/09/1| Visible (Bands 1–7, 9 OLI) | UTM        | 36       |
|      |                       | GN01                    | 2014/09/1| Visible (Bands 1–7, 9 OLI) | UTM        | 36       |
| 2016 | Landsat 8             | LC81680812016280L       | 2016/10/0| Visible (Bands 1–7, 9 OLI) | UTM        | 36       |
|      |                       | GN01                    | 2016/10/0| Visible (Bands 1–7, 9 OLI) | UTM        | 36       |
| 2018 | Landsat 8             | LC81680812018301L       | 2018/10/2| Visible (Bands 1–7, 9 OLI) | UTM        | 36       |
|      |                       | GN00                    | 2018/10/2| Visible (Bands 1–7, 9 OLI) | UTM        | 36       |

depict stable light. Therefore, the cloud cover, stray lights, lightning, and lunar illumination are filtered out of the images available for download.

The USGS Earth Explorer website allows for viewing data before retrieving, ensuring that most suitable images were downloaded. Landsat 7 images used for the year 2012, are known for errors, but this was avoided by looking for an image with an earlier date than the other years but in the same season. The dates for the other years were late in the year, October/November, to cover all the changes throughout the year, but for 2012 the image retrieved was for February because it was the most suitable image to use for that year in terms of cloud cover and other errors.

#### 2.3.2 Post-processing

The post-processing of the nighttime images involved masking the whole frame of the images using the study area shapefile to ensure that the classification to only focused on EMM municipality. This was done in ArcGIS 10.7. using the clip tool found under the raster processing tools. Before clipping the Landsat images, the bands were composited; this process is called image enhancement. For Landsat 7, bands 3, 2, and 1 were used to get the natural look of the image, and for Landsat 8, bands 4, 3, and 2 were used.

#### 2.4 Satellite data LULC classification

Training sites used in the classification of Landsat images were collected using a basemap, which is readily available in ArcMap 10.7.1 due to the travel restrictions as per lockdown regulations which restricted travelling. 20 training sites were collected for each class with totalled to 100 training sites. This was done through the help of visual perception coupled with previous ground experience and information of the area. The training sites collected were for the five LULC classes: commercial areas, built-up areas, recreational areas, vegetation cover, and transportation routes. These classes were adapted from the Anderson classification system [22]. The commercial areas are areas where commercial activities (activities that generate economy in the area) occur. These areas can include shopping centres (retail businesses), services trading areas. The built-up area is made up of residential areas are areas where people reside. These can be their owned homes, rented apartments (flats) or townhouses, industrial areas, and different institutions. Recreational areas are entertainment areas, mostly outdoor entertainment such as stadiums, parks, beaches, etc. Vegetation-covered areas are areas where agricultural activities take place, such as farms, forestry, where there are also just open fields covered by different vegetation, etc. The transportations routes are the roads, railway lines, airports, harbours (harbours mainly involve water as a mode of transport, which explain why water was classified as transportation in the maps of light sources (LULC Maps) to follow [22, 23]. Further description of these LULC classes can be seen in Table 2.

#### 2.5 Data analysis

The data analysis involved reclassifying the NTL imagery, the supervised image classification using maximum likelihood algorithm, and the change detection. The NTL images were reclassified using the light pollution classes adapted from the study done by Prastyo and Herdiwijaya [2]. The original table is shown in Table 3. This table was adapted in this study considering the smallest to largest radiance values in Nw/cm²sr units in each NTL image.

The reclassification of the images was done using the reclassification tool found under the spatial analyst tools of the ArcGIS 10.7. Each image was loaded onto the tool, and the classification values of each class from very low to very high were manually entered on the classified table of the tool. Each of the radiance values in the images was
Table 2  LULC Classes

| Class       | Description                                                                 |
|-------------|-----------------------------------------------------------------------------|
| Commercial  | 1. Shopping center                                                          |
|             | 2. Central Business District (CBD)                                           |
|             | 3. Advertisement board lightings                                             |
|             | 4. Hotels, resorts, lodges, etc.                                             |
| Recreational| 1. Stadiums                                                                 |
|             | 2. Swimming beaches                                                          |
|             | 3. Golf courses                                                             |
|             | 4. Theme Parks (Entertainment)                                               |
| Built-up    | 1. Residential areas                                                         |
|             | 2. Industrial areas                                                          |
|             | 3. Educational institutions                                                  |
|             | 4. Health institutions                                                       |
|             | 5. Other institutions, etc.                                                  |
| Vegetation  | 1. Agricultural lands                                                        |
|             | 2. Orchards                                                                 |
|             | 3. Farms                                                                    |
|             | 4. Forestland                                                                |
|             | 5. Any vegetation cover                                                      |
| Transport   | 1. Roads                                                                    |
|             | 2. Airport facilities                                                        |
|             | 3. Railroad facilities                                                       |
|             | 4. Harbour                                                                  |

Table 3  Light pollution classes

| Class     | DN values (109 Nw/cm²/sr) | Colour |
|-----------|---------------------------|--------|
| Very low  | -0.13-0.90                |        |
| Low       | 0.91–3.40                 |        |
| Medium    | 3.41–8.37                 |        |
| High      | 8.39-18-16                |        |
| Very high | 18.20-86.01               |        |

Classification was used to classify the image into the five land-use classes (Table 2). The training sites that were collected earlier were used for this process. The algorithm used under the supervised classification was the maximum likelihood algorithm that groups the pixels according to the nearest or similar pixel value they fall into. Each class had its different spatial characteristics, such as where they are located, activities taking place on them, the area they cover, etc. Those characteristics are used to classify the commercial area, built-up area, recreational area, vegetation, and transport routes classes, respectively. These include areas that are considered to have activities or areas that use artificial light, which may lead to the occurrence of light pollution.

2.6 Accuracy assessment

Error matrix accuracy assessment was used to access the accuracy of LULC classification. The accuracy of these maps was found to be 80% and above which is the accepted level of accuracy in LULC classifications. Light pollution maps' accuracy was assessed using a conventional approach method where comparison of LULC maps and light pollution maps was done. Light pollution classes were linked to LULC classes. According to Abdelkareem et al. [5], the commercial and built-up areas of the LULC classification are the classes that are most likely to lead to light pollution occurrence. This argument was used to classify or group the commercial and built-up areas as classes that are most likely to lead to very high and high light pollution occurrence. The recreational and transportation classes were classified as classes that could lead to the medium occurrence of light pollution, and the vegetation classes to lead to the very low and low light pollution occurrence.

To further support the accuracy obtained from the procedure above, the cross-section profile that was done for each year using the season that had the highest light pollution was used. These profiles provide an overview of the interaction between the light pollution classes and the LULC classes. These cross-section profiles can be seen in Figs. 2, 3, 4 and 5. The cross profile done across the EMM confirms that the different LULC classes can strongly determine and influence the occurrence of light pollution. The spikes seen on the graphs show which classes mostly contribute to the light pollution, a class with more and high spikes proves to be on high classes of light pollution (4 and 5), which are high and very high classes, and those that relate to a 1 and 2 show very low and low light pollution classes. Further, regression analysis was conducted on TerrSet, where light pollution was analysed as dependent on the LULC classes, and a graph was produced to assess the influence of different LULC classes on occurrence of light pollution.

3 Results

3.1 Light pollution in EMM

The occurrence of light pollution in EMM was classified into five different classes using a study done by Prastyo and Herdiwijaya [2] to adapt and classify light pollution. These classified light pollution into very low, low, medium, high, and very high classes. These classes were identified for each year for the past seven years for each season in the year. This led to four maps presenting the summer, autumn, winter, and spring seasons each year. These will help with showing the significant seasonal variations in lighting. The Figures presented in Figs. 6, 7, 8 and 9 show the light pollution classes for each season. These figures grouped the different seasonal maps into one frame to show the variations in each year.
The accuracy assessment of the light pollution maps when comparing the analysis results with the ground information proved to show similar information, meaning the maps’ depiction is acceptable. The accuracies for all the
light pollution maps were above 80%, which according to Abdelkareem et al. [5], is the accepted level of overall accuracy for a classified map to be used to get results in a study. It is known from the previous studies that light pollution is mostly emitted from the urban areas where that are urban residential areas and where the commercial activities take place. This is also the case with EMM because when the place is surveyed on google earth, it also shows the same areas where we see the very high and high pollution classes.

3.2 Sources of Light Pollution
LULC classification was done to identify light pollution sources over the EMM. This was meant to show which classes of land use contribute to light pollution the most. The land use classes used to classify the map were adapted from the Anderson Classification System [22]. They include the commercial area, built-up area, recreational area, vegetation, and transportation routes. These classes were
Figure 10 shows the maps depicting the land use classes and identified for the past seven years in the interval of two-year. Figure 10 shows the maps depicting the land use classes and
where they are located in the EMM.

In Fig. 10, the main classes that contributed to light pollution are: [classification of LULC classes provided, including very low, low, medium, high, and very high levels of light pollution].
pollution when the land use maps were correlated with the light pollution map were observed to be commercial, built-up, and recreational land uses contributed the most. The maps’ analysis observed development in built-up and commercial areas, which might contribute to the changes in light pollution observed during the study. The vegetation class and transportation contributed moderately to less in the occurrence of light pollution in the EMM. Each class’s contribution or the discovery of the light pollution sources was analyzed by observing the location of each class of land use and considering the location of the light pollution classes along the same area in the municipality map.

Table 4 shows the percentage coverage of each LULC class over each year to attribute the relation of light pollution sources to the increase or decrease of light pollution.

The regression analysis showed a strong positive relationship between LULC and L.P. ($R = 0.698$) with a coefficient of determination of 49%. Thus, the LULC could strongly determine the level of light pollution. This can be seen in Fig. 11.

### 4 Discussion

The use of NTL data in social and natural sciences has been getting more recognition over the years. The particular reason for this is that NTL data is being made available through different sources and captured by different satellites. Another reason for this stated by Elvidge et al. [12] is that NTL provides a special perspective to human activities relating to the use of artificial light at night. Even though the data is abundant, there is still a dearth of studies using it to do their research in African countries [1]. Adelabu and Olusola [10] analysed top 50 and top 100 countries when it comes to publishing in the use of NTL data and African countries were not found in these lists. Research applications in Africa are still lacking when concerning the applications of NTL data. Although this is the case, African urban areas also forms part of areas affected by the rapid economic growth and urbanization, which are the most contributors to light pollution [10].

Light pollution has been reported in South Africa in the past reports, but few studies scientifically assess light pollution extent and intensity. Maree and Naidoo [8] suggested that more studies on light pollution in South Africa need to be conducted to assist with understanding it in depth. The methodology used in these studies is not put clearly to create the foundation for future reference when conducting similar studies. This was seen in a study done by Drescher and Consulting [24], where he was looking at the occurrence of light pollution throughout the country. It is for this reason that the current study has been conducted.

#### 4.1 Light pollution in EMM

The classification of light pollution to discover its occurrence was done by dividing its occurrence into five different classes. The maps produced were from 2012 to 2018; in these maps, each year had a map for each of the four seasons found on the southern hemisphere of the earth. The light pollution mapped in these maps was done using the radiance depicted by the VIIRS DNB imagery. The radiance

| Area Coverage in Percentage of LULC | Area 2012 | Area 2014 | Area 2016 | Area 2018 |
|-----------------------------------|-----------|-----------|-----------|-----------|
| Commercial                        | 24%       | 25%       | 30%       | 30%       |
| Recreational                      | 2%        | 3%        | 3%        | 4%        |
| Built-up                          | 31%       | 36%       | 40%       | 45%       |
| Vegetation                        | 37%       | 32%       | 23%       | 16%       |
| Transportation                    | 5%        | 4%        | 4%        | 6%        |
shown on the map is correlated with the amount of artificial light found on the ground. The higher the radiance value on the image, the higher the brightness of the imagery. It was discovered that very high light pollution is found at the east side of the municipality where the municipality’s main city, Durban, is found.

The main focus of light pollution starts from the city center and spreads out to its outskirts. As you move away from the city, light pollution decreases from very high to high, to medium, to low, and very low. This is shown by the produced maps presented in the results section (Figs. 6, 7, 8 and 9). A similar case was witnessed by Nurbandi et al. [25] when they investigated light pollution over Gajah Mungkor reservoir and Yogyakarta City in Indonesia. They discovered that there was more light pollution over the city than over the reservoir located in a non-urban area. A study by Prastyo and Herdiwijaya [2], which has been mentioned before in this study, also showed that high light pollution mainly occurs in cities and urban areas.

Light pollution has been a growing concern worldwide over the years [26]. Light pollution seems to be growing over the years because more light infrastructure is being made available to many people in different areas. Economic developments in a region are the main factor of light pollution. This is also the case with EMM, found in a developing country, South Africa. South Africa has been developing over the years in terms of economic and social development. Although it is not one of the developed countries; looking at it compared to other African countries, it is doing much better, and it seems to be growing. EMM has been growing over the years in terms of the service it is rendering to the communities. The increase in light pollution associated with the development in the area was also seen in China when a study on quantifying light pollution was done in 2016 by Nurbandi et al. [25] and other researchers.

In China there is an increase in the number of artificial lights detected at night hence an increase in light pollution. Light pollution is also found mainly in areas where there are night activities. Hence, it is mostly found in urban areas rather than rural areas as there is not much happening at night [25]. Jiang et al. [26] also shared same sentiments as they discovered that the increase in light pollution was in cities and non-residential areas have very little to no pollution at all. Also, the area’s geographical characteristics can account for the occurrence of light pollution in certain areas. Areas that are mountainous and hilly do not have much light pollution compared to areas in basin-like areas [27]. This is also the case with the results are attributed by the description of the places where each light pollution class is underlying EMM, the outer skirts of the municipality are mainly mountainous areas with only vegetation hence no light pollution detected.

4.2 Sources of Light Pollution

In trying to find ways to discover the sources of light pollution in EMM, LULC classification was the best technique to follow. This was done because Chalkias et al. [27] stated that light pollution mainly comes from places associated with human habitation and different structures and activities that humans embark on. The study area then classified five LULC classes that dominate the area of EMM. The maximum likelihood method was used to classify a map of each year that the light pollution classes were also classified. According to LULC maps, the main sources of light pollution were the built-up area and commercial areas. These are the areas found in and around Durban, where most of the economic activities occur. Kuechly et al. [28] and Pun et al. [29] also mentioned the same sentiments in their study when they said that light pollution mainly occurs in areas where there are settlements and economic activities associated with the use of artificial light at night.

The areas used for recreational purposes also contribute to light pollution but not as much as built-up and commercial areas. It was also observed from the LULC maps presented that the land covered by vegetation has the lowest light pollution occurring on it. The particular reason for this is that the agricultural activities which are part of the vegetation in EMM are mostly farming crops and forestry. These types of agriculture do not require much use of artificial light at night. Another study done in Flagstaff, United States, investigated the different sources of light pollution, and the results found there attested to the results mentioned above. They assessed land use classes such as public spaces, commercial areas, residential areas, sporting or recreational areas, and industrial areas. It was discovered that commercial areas and built-up areas are the most contributing sources of light pollution. The lighting causing light pollution in these three areas can be from the light spilling out of the commercial shopping center windows and the street lightings [17].

Different activities use different types of artificial light; hence the light pollution classes are not the same in the EMM. The different NTLs do not emit the same radiance, and they contribute differently towards light pollution. In essence, most light pollution in residential areas comes from the streetlights, household lights, with other artificial light sources in these areas being advertisement boards for the commercial industry, decorative lights, and sometimes household lights. These form part of the types of light that can be detected by the NTL data capturing satellites.
5 Conclusion

Covid-19 pandemic made the study to face a lot of challenges, but nonetheless remote sensing advancements made the study a success. Travelling to the field was not possible for effective verification of results. Concluding inferences; the use of NTL data is receiving more interest from researchers, especially in the natural and social sciences fields. This type of data is associated with the use of artificial light at night, which is also seen growing as more areas worldwide are getting access to lighting infrastructure associated with the region’s economic development. NTL data can be used to study different subjects such as urbanization, tracking economic development, and light pollution. This study used NTL data to study light pollution which can affect the night sky quality, human life, and the environment. This study discovered that the light pollution is mostly concentrated in the city centre of the municipality, Durban, compared to municipality’s outskirts. The main sources of this light pollution are built-up and commercial area. It can be concluded that this is because of human activities that utilize artificial lights at night. These activities can be the lighting used to in the streets, commercial boards, light from the commercial shopping areas, and the light used in the industrial areas. Going forward, with the recent development in the cloud-based platforms such as Google Earth Engine (GEE) conducting studies such as this one can be done effectively and will less challenges. This platform provides free access to different datasets which can be utilised to overcome short-comings of traditional methods used in this study. It is therefore recommended for such platforms to be considered.

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