Ersa
Economic Research Southern Africa

What luminosity data can and cannot reveal about South Africa's urban economies

Discussion Document 10

APRIL 2023

Takwanisa Machemedze

About ERSA’s Discussion Documents

Discussion documents are generally solicited pieces on topical issues of relevance to the national economic debate. The intention is to provide a summary of the issue, accompanied by a discussion about its relevance, importance, and way forward in South Africa. Generally, these are narrative driven contributions, relying on existing work and high-level analysis.

We provide the opportunity for contribution from all relevant perspectives, and therefore these papers do not represent a position by ERSA, its associates, or funders on the identified issues.

We hope that through this we can contribute to a more constructive and informed economic debate. We are particularly interested in hearing your thoughts and comments on these contributions. Please feel free to contact us directly or through LinkedIn. If you feel that you have a contribution that you would like to be part of this series, please contact us directly at research@econrsa.org

Matthew Simmonds
Director

What luminosity data can and cannot reveal about South Africa's urban economies

Executive summary

1. Background

In 2015, the United Nations adopted 17 Sustainable Development Goals (SDGs), providing a shared framework for "peace and prosperity for people and the planet, now and into the future" (United Nations, 2015). However, tracking progress towards these goals using reliable data, particularly in developing countries, has been challenging. As a result of challenges faced in tracking development, the UN Secretary-General's Independent Expert Advisory Group (IEAG) called for a "data revolution" to help achieve the SDGs (UN IEAG, 2014). A data revolution involves supplementing traditional sources of official statistics with innovative data sources. The latter includes remote sensing data captured by satellites. The remotely sensed data have been found to provide reliable development measures in contexts where other measures do not exist or the data quality cannot be trusted. One advantage of the remotely sensed data is that they can be disaggregated at various levels, such as global, national, sub-national and even villages. The remotely sensed data are also consistently measured over time and are not affected by boundary changes of administrative units which affect comparison of survey-based data over time. However, the reliability of remotely sensed data to track development must be evaluated against ground-based, traditional sources of official statistics such as censuses and surveys.

1.1 Purpose of study

Nighttime lights (satellite images of Earth at night) provide footprints of human activities on the Earth's surface. They signal night lights from cities, towns, and other sites with persistent lighting, such as gas flares. Therefore, the variation in the night lights across space and time can be used to track various urban dynamics. We report on what nighttime lights/luminosity data reveal about the following key dynamics for South Africa’s urban economies:

i) Change and variation in urban extent,

ii) Growth and variation in urbanisation,

iii) Change and variation in selected socio-economic indicators, such as poverty, inequality, and access to electricity.

We monitor these relationships at the second sub-national level (district councils and district municipalities) in South Africa.

1.2 Methods

1.2.1 Data

We use nighttime light data from the Operational Line-scan System (OLS) sensors onboard the satellites from the Defense Meteorology Satellite Program (DMSP), known as DMSP-OLS. The data comes from six satellites (F10, F12, F14, F15, F16, and F18) over 22 years (1992-2013), resulting in 34 satellite years. The data from the DMSP-OLS satellites are observations of the brightness of nighttime lights. The DMSP-OLS data products are produced as geocoded imagery with a pixel resolution of 30 arc seconds (approximately 1km x 1km). The DMSP-OLS data have several limitations identified and documented in the literature. The problems include blooming or overglow of lights to pixels adjacent urban cities which leads to the overestimation of lit areas, night light saturation in urban cores resulting in the loss of heterogeneity in the brightest places, and temporal inconsistency, making it difficult to compare the data in a time series.

In this study, we corrected for the lights overglow using deblurring methods developed by Abrahams et al. (2018) and for the temporal consistency using inter-calibration methods proposed by others (Elvidge et al., 2014; Elvidge et al., 2009). After correcting for some of the limitations described above, we derive the "area of lights" (AoL) that counts the number of lit pixels with digital numbers greater than zero within a defined geographical space or polygon. The night lights are assumed to identify footprints of persistent human activities and we presume that the lit areas are established urban areas. We also compute the Gini coefficient of inequality for the lit pixels for each district council.

We use South African census data from 1996 and 2011. From the censuses, we derive urban extent by aggregating the urban or non-urban classifications of enumeration areas (EA) in 1996 and sub- places (SP) in 2011. We aggregate EAs and SPs to the District Council level, which is our measurement unit. We derive the urban population from the identified urban EAs/SPs. For each district council, we also derive the number of households that use electricity for lighting and households whose per capita income was below the upper-bound of the national poverty lines derived by Statistics South Africa (Lehohla, 2008; Statistics South Africa, 2019). We also use the household income per capita to compute each district council's income Gini coefficient of inequality.

1.3 Findings

We first compared the accuracy between census urban classification of EAs/SPs against night lights urban EAs/SPs with at least a lit pixel. The confusion matrix between the two sources, census and night lights, shows an accuracy of the urban/non-urban classification of about 77% for EAs in 1996 and 86% for SPs in 2011. We aggregated the area size of the EAs/SPs from both census urban classification and night lights count of lit pixels. We found that the census urban definition derives a more extensive area size, 3.02% in 1996 and 3.04% in 2011, compared to the nighttime lights, which was 0.77% in 1996 and 0.96% in 2011. Between 1996 and 2011, the census urban extent grew by 0.5%, and the nights lights urban extent grew by 25.4%. In other words, the size of lit areas in 1996 had increased by a quarter in 2011.

We also investigated what the luminosity data reveal about change and variation in urbanisation/urban extent, growth, and variation in the composition of the urban population, change and variation in selected socio-economic indicators, such as poverty, inequality and access to electricity. Our results show a weak but significant positive relationship between South African census urban area size and lit areas derived from the night lights. We also observed a strong and significant positive relationship between the census urban population and the night lights lit areas. The estimated number of households using electricity for lighting derived from the censuses has a strong positive association with the night lights lit area. The proportion of households whose income is below the upper-bound of the poverty line is negatively associated with lit area derived from the night lights. That is, the proportion of poor households decreases as lit area increases. There was no significant association between household income-based Gini coefficient and the night lights-based Gini coefficient.

1.4 Conclusions

There is a weak association between the DMSP-OLS night lights lit area and South African administrative urban extent. This is probably because of South Africa's unusual urbanisation process inherited from Apartheid-era spatial engineering. In some cases, there is no consistent urban or city system such that some dense rural settlements emit night lights and appear as urban areas. The lit area measure performs well at predicting the urban population and the number of households using electricity for lighting at the district level. This association is expected because the night lights identify footprints of human presence and activities. The night lights performed poorly at predicting poverty rates and inequality. The probable explanation is that night lights from urban areas reflect the provision of public services rather than household socio-economic status. Therefore, the night lights are not good at measuring some of these socio-economic variables.

1.5 Recommendations

We recommend replicating this study, comparing the forthcoming 2022 South African census results against the superior VIIRS-DNB night lights data. This would help to evaluate the usefulness of the VIIRS-DNB data using detailed census data. We observed some mismatches between the census urban and night lights lit area. Among these are EAs and SPs that did not match. Night lights could help identify informal settlements and how they have evolved, helping to identify marginalised populations.

2. Introduction

The availability of reliable data at various sub-national levels is crucial to the monitoring and achievement of the United Nations (UN) sustainable development goals (SDGs) (United Nations, 2015). Several of the SDGs depend on demographic data obtained from household-based censuses and surveys. Many of the SDG targets also use demographic data for denominators. However, most developing countries have limited data to measure various socioeconomic indicators at the local level. As a result, the UN Secretary-General's Independent Expert Advisory Group (IEAG) called for mobilising the data revolution for sustainable development. They proposed the idea of complementing traditional data sources with new data sources to improve the monitoring of SDGs (UN IEAG, 2014).

Researchers from various disciplines have turned to alternative data sources, such as remote sensing captured by satellites, to track development. One advantage of remotely sensed data is that they can be disaggregated at various levels – global, national, sub-national and even villages. One prominent example of remotely sensed data that has been applied to capture socio-economic mechanisms are the nighttime lights (NTL) or night lights. Previous studies have shown promising results on the application of night lights emission data to Monitor human settlements (Elvidge et al., 1997a; Lu et al., 2008), map urbanisation/urban extent (Imhoff et al., 1997; Small et al., 2005), estimate urban population and population density (Sutton et al., 2001; Elvidge et al., 1997c), estimate energy and electricity consumption (Amaral et al., 2005; Elvidge, Baugh, Kihn et al., 1997c), and socio-economic activities such as GDP (Elvidge, Baugh, Kihn et al., 1997c), poverty rates (Wang et al., 2012), spatial inequality (Elvidge et al., 2012) and among other measures reviewed elsewhere (Levin et al., 2020; Huang et al., 2014).

In 2015, the United Nations adopted 17 Sustainable Development Goals (SDGs) that provide a shared framework for "peace and prosperity for people and the planet, now and into the future" (United Nations, 2020). The 17 goals include the stand-alone SDG Goal 11 (SDG 11), which aims to "make cities and human settlements inclusive, safe, resilient and sustainable". SDG 11 highlights that sustainable urban development and management are essential for people's quality of life. It is, therefore, important to understand the dynamics of urban economies for spatial and temporal variations. In this study we examine what nighttime lights data can reveal about South Africa's urban economies and how these relationships have evolved over the past three decades. We also examine how changes in urban night lights are related to other measures such as poverty rates (related to Goal 1), electricity access (related to Goal 7) and income inequality. Specifically, we report on what luminosity data reveal about the following key dynamics:

iv) Change and variation in urban extent,

v) Growth and variation in urbanisation,

vi) Change and variation in selected socio-economic indicators, such as poverty, inequality, and access to electricity.

We monitor these relationships at the second sub-national level (District Council (DC)/District Municipality) in South Africa.

3. Nighttime lights data

Nighttime lights data are satellite observations of detected artificial night lighting on the Earth's surface. There are two main sources of the nighttime lights data which are: (i) the Operational Line- scan System (OLS) sensors onboard the satellites from the Defense Meteorology Satellite Program (DMSP)[1] commonly known as DMSP-OLS (Elvidge et al., 1997b) and (ii) the Visible Infrared Imaging Radiometer Suite Day-Night Band (VIIRS DNB) sensor onboard the Suomi NPP (SNPP) and National Oceanic and Atmospheric Administration (NOAA)-20 satellites from the Joint Polar Satellite System (JPSS), a partnership between the National Aeronautics and Space Administration (NASA) and NOAA (Elvidge et al., 2017).

The U.S. Air Force launched the DMSP program in the mid-1960s to observe weather-related indicators and cloud cover for short-term weather forecasts. It was then discovered that the OLS sensors could capture low-light imaging of human activities (Croft, 1978). The data were then digitised and made freely available by NOAA's National Centers for Environmental Information (NCEI) (previously known as the National Geophysical Data Center (NGDC)) (Doll, 2008). NOAA/NCEI has archived the DMSP-OLS annual composites from 1992 to 2013. The VIIRS

[1] https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html

instrument was launched in 2011 and can detect dim light sources at night. The VIIRS has several improvements to the limitations of the OLS and is considered to collect high-quality nighttime lights data (Elvidge et al., 2013). Monthly composites of the VIIRS[2] are available from April 2012 to May 2022, and annual composites from 2012 to 2021 (Elvidge et al., 2021). Data collected by either of the sensors provides a measure of the brightness of nighttime lights observed on the Earth's surface. However, the data from the two sensors are different in many ways, and we discuss the strength and limitations of the two data sources in the section to follow.

3.1 DMSP-OLS vs VIRS

The DMSP-OLS nighttime lights data are an unanticipated bi-product of weather monitoring data and their application in the social sciences suffers several limitations. Elvidge, Baugh, Zhizhin et al. (2013) compare the DMSP-OLS and the VIIRS products side-by-side. The shortcomings of the DMSP-OLS fall into two groups: spatial accuracy of lit areas and temporary comparability/consistency of brightness over time (Doll, 2008). For spatial accuracy, the DMSP-OLS are well known for overestimating the lit area, commonly known as "blooming" or "glowing". The three main reasons cited for this problem are coarse spatial resolution, the large overlap between pixels and errors of geolocation. The DMSP/OLS has a nominal spatial resolution of 2.7 km, which can be too coarse to characterise inter-urban variability. Due to the way the satellite sensors scan the ground, there is some overlap between pixels such that large areas may show as lit than what is actually on the ground (Elvidge et al., 1996). It is also observed that the DMSP-OLS have geolocation errors introduced when transforming the observed values onto grids of the Earth's surface (Tuttle et al., 2013). A combination of these factors results in overestimating lit areas than locations with a light source. It is argued that the impact of the spatial errors can be minimised by applying the data to larger areas, such as countries or the first and second sub-division, such as provinces or districts (Gibson et al., 2020).

[2] https://eogdata.mines.edu/products/vnl/

For temporal consistency, the DMSP-OLS data products are not comparable over time (Elvidge, Hsu, Baugh et al., 2014; Elvidge, Ziskin, Baugh et al., 2009). The radiometric resolution of the DMSP/OLS data is constrained to 64 digital number (DN) values (6 bit – quantisation), resulting in saturated pixel values in urban centres, and details of variation of the top lights are lost. Another problem in the DMSP-OLS night lights data is the lack of onboard calibration resulting in radiometric quantities that are not consistent across space or time and, as a result, making a time-series analysis difficult.

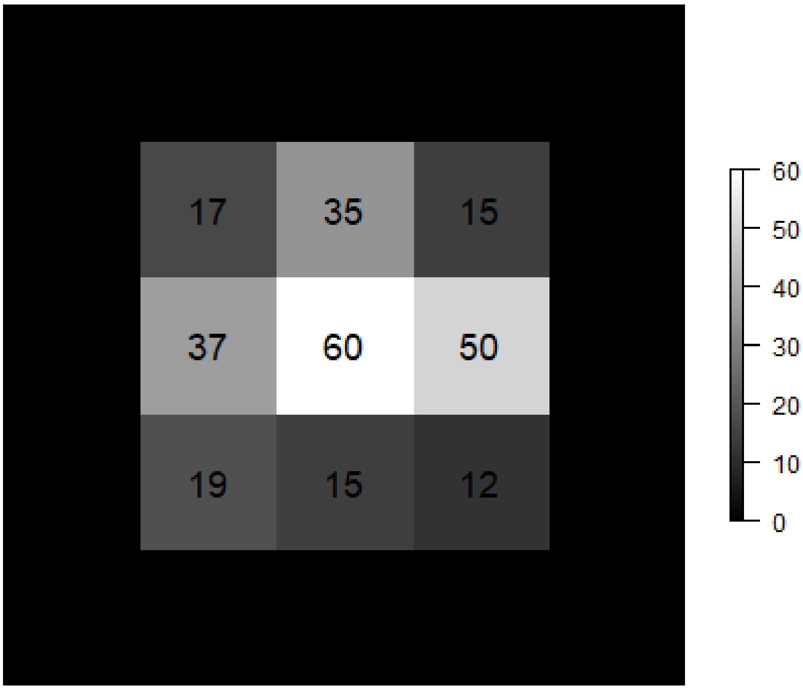
On the other hand, VIIRS-DNB offers several improvements to nighttime light imaging compared to its predecessor, the DMSP-OLS (Elvidge, Baugh, Zhizhin et al., 2013). The VIIRS-DNB has improved spatial accuracy with an increased spatial resolution of 742mx 742m compared to 2.7km x 2.7 km in DMSP- OLS. The blooming effect of the OLS has also been reduced mainly in the VIIRS-DNB (Sahoo et al., 2020). For temporal consistency, the VIIRS-DNB has onboard calibration, producing the nighttime lights intensity values in radiance units compared to unitless DN values. The VIIRS-DNB sensors also have a higher radiometric quantisation of 14-bit (such as a wider range of values with 16 384 levels) compared to 6-bit in DMSP-OLS (64 digital values). The large dynamic range in the VIIRS-DNB overcomes the problem of saturation in urban cores, and they can also detect dimmer lights because of the wider detection range (Elvidge, Baugh, Zhizhin et al., 2017; Elvidge, Baugh, Zhizhin et al., 2013). While the VIIRS-DNB products are more accurate, the DMSP-OLS data have been widely used because they have been available for an extended period.

3.2 The measure of nighttime lights

The nighttime lights data described above are produced in the form of geocoded imagery with a pixel resolution of 30 arc seconds (approximately 930m x 930m) for the DMSP-OLS and 15 arc seconds (about 465m x 465m) for the VIIRS-DNB, at the equator (Gibson, Olivia and Boe - Gibson, 2020). The geocoded data can be mapped to most places on the Earth's surface. Several measures can be derived from the night lights imagery. Figure 1 illustrates an area covering 25 square pixels

(5 x 5 pixels). In this illustration, the outside dark pixels have values of zero and the lighter pixels have values greater than zero.

Figure 1: An example of nighttime lights data



We can assume that the numbers within the pixels in Figure 1 are DN values representing observed brightness from the DMSP-OLS. Taking pixels with values greater than zero to be urban/lit areas, several key variables can be derived. Using the notation from Addison and Stewart (2015), some of the variables that can be derived are:

(i) the number of lit pixels within a defined geographical space or polygon, and this will be referred to as the "area of lights" (AoL);

(ii) the average of digital numbers (R) of lit pixels within the polygon; and the

(iii) "sum of lights" (SoL) which equals the sum of the digital numbers of all lit pixels. The sum of lights, SoL, also equals the area of lights, AoL, multiplied by the average of DN values, R.

From the illustration in Figure 1, AoL includes 9 pixels with values greater than zero, the average of the lit pixel values (R) is 28.89, and the sum of the lit pixel values (SOL) is 260.

In addition to these measures, researchers have used measures like the maximum digital number or the average digital number within an area or per population size.

3.3 Proposed corrections to the DMSP-OLS series

Inter-calibration

One problem with the DMSP-OLS night lights data is that the sensors degrade over time and there is no onboard calibration of the brightness observations. As a result, night lights values from two different satellites from the same year are different and incomparable. Some scholars have developed inter-calibration methods to normalise the observed values, and this is recommended if one wants to compare the night lights observations in a time series (Elvidge, Ziskin, Baugh et al., 2009; Mukherjee et al., 2017). One approach utilised to inter-calibrate the DMSP-OLS is the pseudo-invariant region/pseudo-invariant feature method (Wei et al., 2014), which assumes that there are pixels for which the lights have changed very little over time. The invariant pixels are then used to model an inter-calibration function. For example, Elvidge, Ziskin, Baugh et al. (2009) selected Sicily, an Island in Italy, as the invariant region and used F121999 (sensor F12 from 1999) as the reference data point. Using a quadratic equation model, the nighttime lights from all other satellite years were adjusted to match the F121999 data range. Other proposed inter-calibration methods are the optimal threshold method (Liu et al., 2012), the power-law regression method (Wu et al., 2013), and the ridge line sampling regression method (Zhang et al., 2016).

Top coding

The DMSP-OLS pixel values are constrained to digital values between 0 and 63 because of onboard memory limitations. As a result, details of variation in urban centres are lost as all top lights are coded to be 63. Bluhm and Krause (2022) proposed correcting the top-lights (DN values 55 and above) by fitting a Pareto distribution based on parameters from the 'radiance calibrated' DMSP-OLS series that was observed for selected years. The top-coding correction improves the variation of the DMSP-OLS night lights in urban cores.

Filtering temporary light

The DMSP-OLS data also have the problem of overglow or blurring the night lights. Abrahams, Oram and Lozano-Gracia (2018) provide a detailed explanation of sensor and data management flaws that lead to geolocation errors, blurring, and top coding. They demonstrated that the blurring follows a symmetric Gaussian point-spread function (PSF) and developed a method to deblur the DMSP data.

This deblurring method greatly improves the DMSP-OLS annual composite images for estimating urban areas. There are also other methods for mitigating the "blooming" effect inherent in the DMSP data that have been proposed by other scholars (Townsend and Bruce, 2010; Cao et al., 2019; Hao et al., 2015)

4. Literature review

In this section, we review literature on the use of luminosity data to assess social and economic change. The nighttime lights sensors measure artificial night lighting by humans, indicating urban extents and human activities. As a result, the night lights data have been applied to assess and estimate various socioeconomic indicators. We review some of the previous research in the following section. This review is not exhaustive of all the literature but demonstrates some research related to our aims and objectives.

4.1 Monitoring human settlement

Since the nighttime lights capture low-light imagery of human activities, one obvious application of the night lights products is to identify human settlements. It is possible to estimate the location, spatial extent, and frequency of occurrence of the night lights. Elvidge, Baugh, Hobson et al. (1997a) applied the DMSP-OLS data to examine the relationship between area lit, population, and energy-related carbon emissions for 52 countries. Consistent with prior studies, Elvidge, Baugh, Hobson et al. (1997a) observed considerable variation between countries in the relationships between lit areas and each population and carbon emissions. The DMSP-OLS nights lights data identifies the location of persistently lit areas of human settlements, but because of the coarse resolution of the data, they overestimate the actual area of human settlements (Small, Pozzi and Elvidge, 2005). To increase the mapping accuracy of the DMSP-OLS night lights, Lu, Tian, Zhou et al. (2008) combined the night lights data and vegetation indices (NDVI) from the MODIS satellite products to map human settlements in south-eastern China. They showed that the DMSP-OLS data might need to be supplemented with vegetation data to produce more accurate estimates and spatial distribution of urban settlements.

4.2 Estimating urban population and population density

In addition to identifying human presence, the potential use of nighttime lights for estimating country and sub-national populations has also been investigated. Elvidge, Baugh, Kihn et al. (1997c) found that the logarithm of the area lit derived from the DMSP-OLS data can explain 85% of the variation in population size for 21 countries. However, they also observed significant outliers in the relationship between lit area and population size. Sutton, Roberts, Elvidge et al. (2001) also used night lights to estimate the total urban population. Using known proportions of the urban population for all countries, their estimated global population in 1997 was 6.3 billion compared to a UN estimate of 5.9 billion. The difference of 400 million people is significant.

4.3 Mapping urbanisation process/urban extent

Scholars have also attempted to estimate the urban extent using night lights. One method uses DMSP- OLS data to determine an optimal threshold of (i) the frequency of detection of lights or (ii) DN value, above which can be considered an urban area (Imhoff, Lawrence, Stutzer et al., 1997; Sutton, Roberts, Elvidge et al., 2001). However, there is no established standard threshold because different places have different levels of development to determine their urbanity. It is argued that higher brightness thresholds generally capture highly developed areas whereas lower thresholds overestimate lit areas to include smaller settlements and agricultural areas (Small, Pozzi and Elvidge, 2005).

Earlier work investigating the relationship between lit areas and urban extent proposed to use night lights thresholds based on the frequency of light detection in an area to eliminate less frequently detected lit pixels (Imhoff, Lawrence, Stutzer et al., 1997; Small, Pozzi and Elvidge, 2005). Imhoff, Lawrence, Stutzer et al. (1997) proposed a threshold of 89% for three US cities, while Sutton, Roberts, Elvidge et al. (2001) avoided the limitations of a single threshold by using a combination of 40%, 80% and 90% for a global analysis. These studies reveal that no single threshold of lit area meets all definitions of urban extent.

Other scholars have explored the DN threshold to estimate urban extent. For example, Small et al. (2011) found that DN thresholds greater than 12 yield relatively consistent results of the slopes of the power law for city size. Using higher-resolution land cover or built-up area maps as a benchmark, Roberts et al. (2015) derived a threshold DN value of 21 to delineate urban areas using the 1996 and 2010 data.

A technical problem with the DMSP-OLS data is the overglow of lights to pixels adjacent to urban cities. If the overglow problem is not carefully considered, it leads to an overestimate of lit areas assumed to be urban areas. Several researchers have developed methods to deblur the DMSP-OLS data (Townsend and Bruce, 2010; Cao, Hu, Zhu et al., 2019; Hao, Yu, Sun et al., 2015; Abrahams, Oram and Lozano-Gracia, 2018). For example, the method by Abrahams, Oram and Lozano-Gracia (2018) substantially improves the overestimation of urban extents 5.5-fold over NOAA's stable lights filtered images, and a 9-fold over the blurred images for a sample of 15 cities.

4.4 Estimating electrification

Nighttime lights imagery data have also been explored for assessing electrification. Elvidge, Baugh, Kihn et al. (1997c) observed that lit areas were highly correlated with electricity power consumption or 21 countries with an R2 of 0.96. Another study on Brazilian urban settlements observed a significant linear relationship between lit areas and electric power consumption with an R2 of about 0.80 (Amaral, Câmara, Monteiro et al., 2005). Some studies have demonstrated that the DMSP-

OLS data can track rural electrification in developing countries up to the village level. It has been shown that the nighttime lights can reliably detect electrified villages when compared with ground-based information from Senegal and Mali (Min et al., 2013), South Africa (Machemedze et al., 2017) and India (Dugoua et al., 2018). The studies found a high correlation between night light brightness and the number of households with access to electricity. Several other studies confirm the close relationship between night light brightness and electrification (Min and Gaba, 2014; Lu et al., 2019).

4.5 Estimating socio-economic activities – gross domestic product, poverty and inequality

Several studies have assessed the relationships between nighttime lights data and socio-economic activities such as gross domestic product (GDP), poverty and inequality. The relationship between nighttime lights and GDP has been studied more, likely as GDP estimates are readily available for most countries. An early study by Elvidge, Baugh, Kihn et al. (1997c) using night lights data for 1994 and 1995 found that the logarithm of the area lit derived from the DMSP-OLS data explained 97% of the variation in the log-transformed GDP for 21 countries. Another study by Sutton and Costanza (2002) observed a high correlation between the sum of the intensity of nighttime light and GDP per square kilometre using 1995 and 1996 data. These studies are based on cross-sectional analysis. Other studies that performed a panel analysis on the relationship between DMSP-OLS luminosity data and GDP concluded that nighttime lights data can add value to the estimation of national statistics of economic activity when this data is of poor quality or not readily available (Chen and Nordhaus, 2011; Henderson et al., 2012). Chen and Nordhaus (2011) noted that nightlights did not estimate well the GDP for countries with low GDP per unit area. Other studies observed that night lights correlate closely with GDP for urban economies compared to non-urban economies. For example, Keola et al. (2015) show that the relationship between DMSP-OLS night lights and GDP for several countries was positive when the share of agricultural activities was less than 20%. This relationship was negative when agricultural activity share increased between 20% and 40%. The authors argue that night lights are not a good predictor of economic activities for agriculture-based economies because agricultural output may increase without necessarily increasing detectable lights captured by the OLS sensors. Bickenbach et al. (2016) observed that the relationship between nighttime lights and GDP was unstable at the regional/ sub-national level within emerging economies such as India and Brazil and for developed economies such as the United States or Western Europe. They argue that the relationship between change in nighttime lights and GDP at the national level as suggested by Henderson, Storeygard and Weil (2012), does not hold at the subnational level. The studies discussed used the older DMSP-OLS data with its several limitations. Gibson (2021) observed that the newer and improved VIIRS night lights data is a better proxy for real GDP with a predictive power of about 80% higher than that for the DMSP-OLS data in a cross-section of NUTS2 regions. Dugoua, Kennedy and Urpelainen (2018) observed that the DMSP-OLS nighttime lights are less reliable for measuring poverty rates derived from the proportion of households with assets. Mirza et al. (2021) compared night lights inequality derived from selected years of the DMSP-OLS and the VIIRS series, and global estimates of income inequality and observed a significant correlation of 0.44. They argue that it is impossible to observe matching estimates because of biases from both data sources: traditional household income and nighttime lights. Weidmann and Theunissen (2021) compared the Gini inequality from the VIIRS to Gini inequality derived from the asset wealth index values from the Demographic and Health Survey (DHS) for several developing countries. They observed a positive but weak relationship between the two measures and argued that this was because of fewer assets related to electricity consumption used in their wealth index. It is also important to note that the weak statistical relationship is likely because night lights from urban areas reflect provision of public services rather than household socio- economic status.

5. Application to South Africa

The application of night lights has also been explored in South Africa. Kroth et al.

(2016) used night lights data as a proxy for electrification to validate their model which correlated enfranchisement and electrification among South African municipalities. They found that lit areas based on night lights had a correlation of 0.47 with the proportion of households with access to electricity. Machemedze, Dinkelman, Collinson et al. (2017) investigated the relationships between the DMSP-OLS night lights and ground-based village-level household electrification across space and time and observed significant variation. Pfeifer et al. (2018) applied the DMSP-OLS night lights as a proxy for economic activity to reveal that investments done for the soccer world cup in 2010 translated to a reduction in the unemployment rate at the municipality level and growth in provincial GDP. Mveyange (2018) analysed the South African data at the district council level and observed that income-based inequality measures (such as the Gini coefficient and the Theil index) significantly correlated with the corresponding DMSP nighttime lights measures. Gibson et al. (2021) used night lights data for 2013 to compare which one of DMSP-OLS and VIIRS was a better measure against various socio-economic variables for the 234 South African municipalities. They observed that the VIIRS data predict the municipality level GDP better than the DMSP stable lights, close results for total employment and that the DMSP-OLS underestimate the Gini and Theil index of spatial inequality. Kleynhans and Coetzee (2021) investigated the association between nighttime light emissions and gross domestic product (GDP) estimates for South Africa. Their results suggested a statistically significant long-term relationship between the two.

5.1 Method

5.1.1 Ground truth data

Our ground truth data is derived from South African censuses conducted in 1996 and 2011. Both censuses coincide with the DMSP-OLS series covering 1992-2013. We could not use the 2001 census data but this was desirable. Table 1 shows the census geography hierarchies for the 1996, 2001 and 2011 censuses.

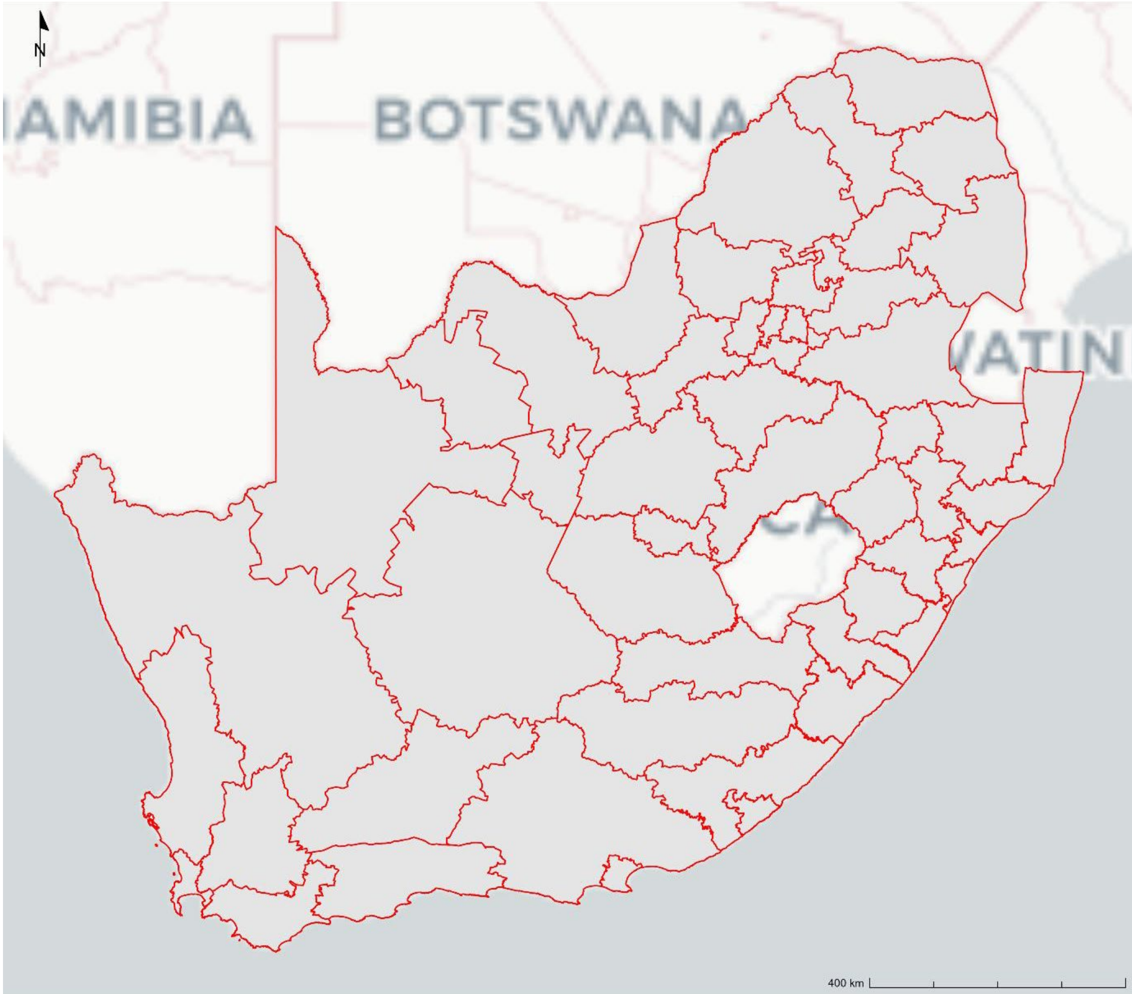
Table 1: Spatial hierarchy of South African censuses – 1996, 2001 and 2011

1996	2001	2011
Provinces (9)	Provinces (9)	Provinces (9)
Magisterial districts (354)	District Councils (52)	District Councils (52)
Enumeration areas (83 126)	Local municipalities (262)	Local municipalities (234)
	Main places (2674)	Main places (14039)
	Sub-places (15966)	Sub-places (22108)
	Enumeration areas (80787)	Small Area Layers (84907)
		Enumeration areas (103576)

From Table 1, an enumeration area (EA) is the smallest geographical unit assigned to a single person to enumerate during a census. The sub-place is the spatial unit one level up from the EA and corresponds to a suburb, ward, village, farm, or informal settlement (Statistics South Africa, 2003a, 2011b). The hierarchies go up until the province, which is the first sub-division level. The enumeration area and sub-place census geography are used to estimate the size of the urban area of each district council, which is our unit of analysis in this study. We achieve this by aggregating the geography type as urban or non-urban for each EA and/or sub-place (SP) as provided in the data. The size of the census urban area for each district council, our unit of assessment, will be compared against the night lights lit area. Figure 2 shows the map of the 52 South African districts used for the 2011 census.

The censuses have publicly available detailed information on household income and electricity access from the enumeration areas (1996) and sub-places (2001 and 2011). Data on household income will be used to derive poverty rates and income inequality, which will both be compared against the night lights lit area size. The following section describes the definition of 'urban', poverty rates, and income inequality.

Figure 2: Map of the 52 district councils used in the South African census of 2011



5.1.2 Urban definition

The delineation of South Africa into urban and rural areas has been challenging (Statistics South Africa, 2003b). The most recent South African censuses conducted in 1996, 2001 and 2011 utilise different definitions of an urban area, which is an important measure in this study. The 1996 census defines urban areas as "areas with local authorities" irrespective of their spatial features. This included an ordinary town or city with formal structures, informal dwellings, mining hostels and hospital and prison institutions (Statistics South Africa, 2003b).

The 2001 census defined an 'urban settlement' as structured and organised, providing water, electricity and refuse removal services and formally planned and maintained roads. Compared to the 1996 census, the 2001 census did not classify enumeration areas into urban and rural (Statistics South Africa, 2003b). Therefore, while the publicly available data for the 2001 census provides information on the EA type (tribal settlement, farm, smallholding, urban settlement, informal settlement recreational area, industrial area, institution, hostel, vacant), it is not possible to encode these into any of the geography types used in 2001, such as urban formal, urban informal, rural formal and tribal area (Statistics South Africa, 2003b).

The 2011 census categorised areas by three geography types: urban area, traditional or tribal area, or a farm area. The geography types are derived from the dominant land use for each EA. There are 10 EA types: formal residential, informal residential, traditional residential, farms, parks and recreation, collective living quarters, industrial, small holdings, vacant, and commercial. These EA types are encoded into urban and non-urban.

For the 1996 census, we use the 2001 census definition of an urban area using the reclassification described by Statistics South Africa (Statistics South Africa, 2003b). The census 2001 itself does not have information on geography type, making it difficult to assign the respective SPs to their urban or non-urban status. Therefore, the 2001 census data was not used for this study. For the 2011 census, we recoded the geo-type provided in the data into urban (urban area) and non-urban (traditional or tribal area, or a farm area).

5.1.3 Urban size

From the procedure above, we can identify urban EAs/SPs. The area of the urban EAs/SPs can be aggregated to the district council level and compared against lit area from the night lights.

5.1.4 Urban population

Similarly, we can aggregate the urban population from each urban EA/SP to the district council level and compare against lit area from the night lights.

5.1.5 Electrification

This variable is defined as the proportion of households with access to electricity in the respective district councils. All censuses ask a standard question about the main type of energy households use for their cooking, heating, and lighting. We are interested in households that use electricity. Using electricity for heating and cooking is considered expensive; some households may not use it for these purposes even if they have limited access to electricity (Thom, 2000). Therefore, we consider using electricity for lighting to be a proxy for access to electricity.

5.1.6 Poverty rates

The South African census provides information on SA household incomes per income bracket. We take the middle of each income bracket to be the average income for the respective households. We then divide the middle value by the number of people in each household to derive a household income per capita. For each district council, we count the number of households that earn less than the upper- bound poverty line derived by Statistics South Africa for the respective years (Statistics South Africa, 2019; Lehohla, 2008). For 1996, we use the upper bound poverty line of R323 (Lehohla, 2008) and for 2011 we use R779 (Statistics South Africa, 2019). While the upper bound poverty line used for 1996 was derived for 2000, others have also applied these same bounds for 1997 (Rogan and Reynolds, 2019).

5.1.7 Inequality

Using the per-capita household income derived above, we compute a per-capita household income Gini coefficient of inequality for each district council.

5.1.8 Nighttime lights data

We used data from the National Oceanic and Atmospheric Administration's (NOAA's) National Geographic Data Center (NGDC). The data comes from six satellites (F10, F12, F14, F15, F16, and F18) over 22 years (1992-2013), resulting in 34 satellite years. The data are freely available from the NGDC website (http://www.ngdc.noaa.gov/dmsp/ download.html). We use data from sensors, F121996 for 1996 and F182011 for 2011.

Three types of imagery are associated with the DMSP-OLS annual average data (Doll, 2008): cloud- free coverage composite, average visible composite, and stable light composite. The cloud-free coverage composite counts the number of images that were considered to create 30 arc second grid cells. The average visible composite are the averages of the digital numbers used to measure night light brightness and these have not been filtered for background noise. The stable lights composite cover lights for cities, towns and other persistent lighting, and background noise has been removed according to NOAA methods. However, the 'stable lights' are observed to overestimate lit area when compared to ground-based information as reviewed above.

Deblurring

We therefore use the average DN data and 'deblur' using the Abrahams, Oram and Lozano-Gracia (2018) procedure. The deblurring method identifies pixels that are persistently lit for a certain proportion of the time, and we use the default value of 20% from their algorithm. We then recode the lit pixels into binary values, such as 1 if lit and 0 if value is 0.

Inter-calibration

We also inter-calibrated average DN values using Elvidge, Hsu, Baugh et al. (2014) procedure. This procedure is meant to bring data from different years and satellites onto the same scale.

Filter background noise

The binary pixels from the deblurring process are then matched with intercalibrated images and used to identify and create a new image with background noise filtered out. This image still has the problem of top coding. However, except for the inequality comparison that uses pixel-level values, most of our analyses utilise the size of the lit area unaffected by the top coding problem.

We derive the night lights measures from the image that has been inter-calibrated and filtered of background noise. We derive the lit area or area of light (AoL) for each district municipality, such as the count of lit pixels from the deblurring procedure. We also compute the Gini coefficient of inequality for the lit pixels for each district council.

5.2 Analysis

We begin by conducting a descriptive analysis. We compare the accuracy of night lights in urban areas based on aggregating lit pixels against census-based urban derived from EAs/SPs. In other words, we check the level of agreement about how many EAs/SPs considered urban in the census have at least a persistently lit pixel(s). We also compare differences in the growth of urban areas according to night lights and the census definition.

We then examine the correlation coefficient (Pearson's r) between night lights lit area, AoL, and census ground truth data, such as urban area size, urban population, electrification levels and poverty rates. We also compare the night lights Gini index against household-income-based inequality derived from census data. For the survey-based measure of local inequality, we compute the Gini inequality coefficient for the per capita household income from the two censuses.

We then conduct a simple linear regression analysis of how much variation in our ground truth variables can be explained by the variation in the night lights data. Some variables are skewed, so we first log-transform the variables and check which relationship provides the best linear fit.

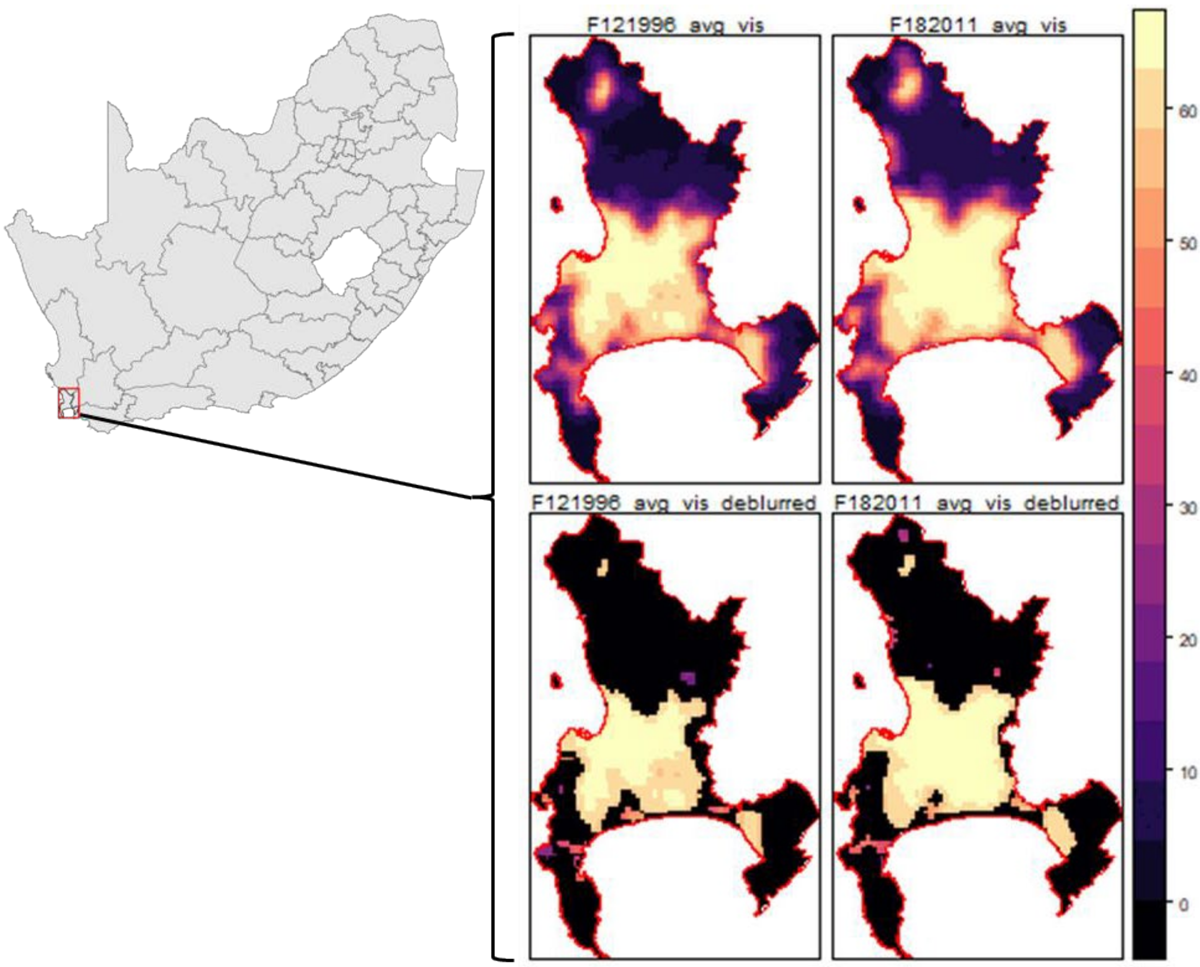
6. Results

6.1 Descriptive analysis

6.1.1 Deblurring

Figure 3 shows the effects of the deblurring method developed by Abrahams, Oram and Lozano-Gracia (2018) on the F121996 (F121996_avg_vis) and F182011 (F182011_avg_ vis) sensors. The average digital numbers are on the top row and the deblurred images are on the bottom row of the map insert. We can observe that the unfiltered image exaggerates the lit area.

Figure 3: Effects of deblurring the DMSP-OLS data – City of Cape Town, South Africa

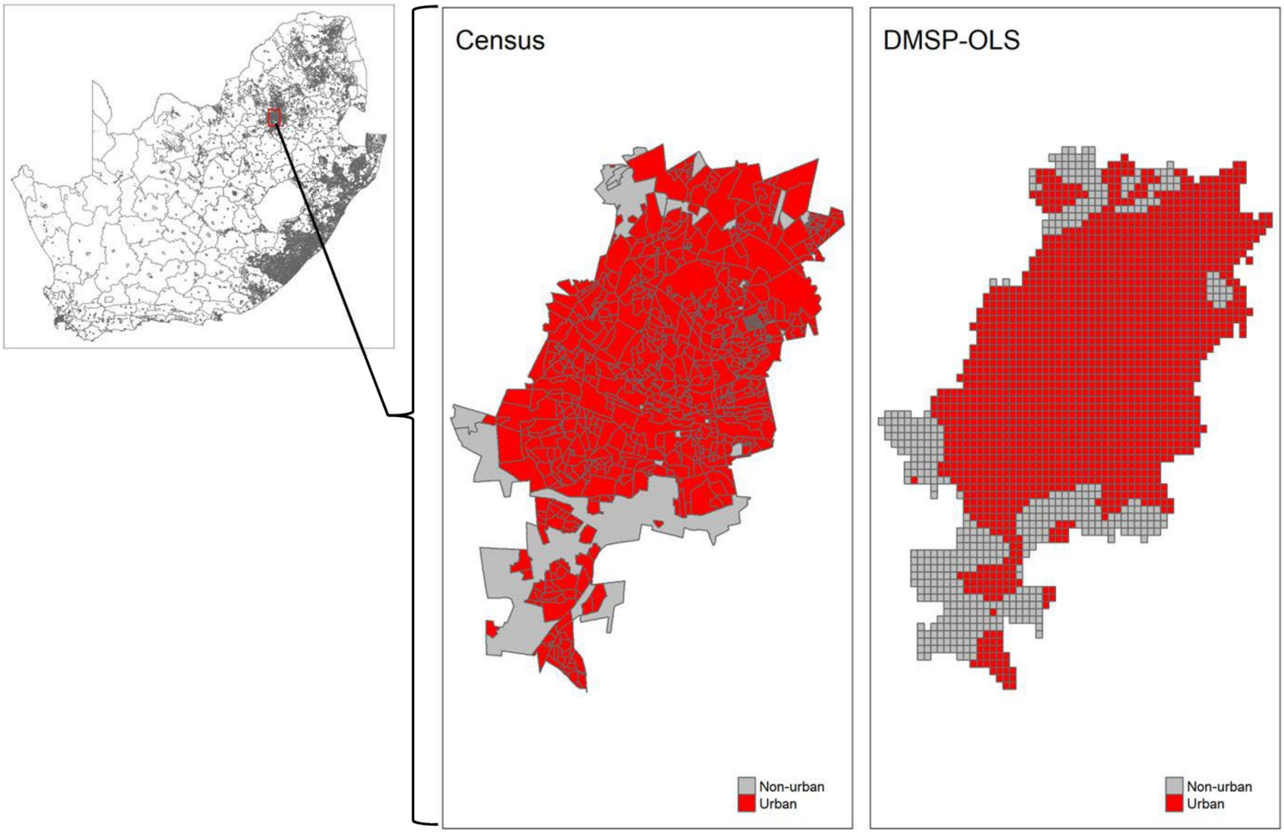


6.2 Nighttime lights and urban extent

6.2.1 Spatial distribution

Figure 4 shows an example of the spatial distribution of urban areas according to the census SPs vs night lights lit area. For the census data, the categorisation of urban is provided in the SuperCROSS community profiles acquired from Statistics South Africa. For the night lights, a deblurred pixel with at least a pixel value greater than 0 is considered urban.

Figure 4: Spatial distribution of urban areas for the City of Johannesburg in 2011: census SP and night lights pixels



For the case of the City of Johannesburg shown in Figure 4, the night lights data traces the outline of the urban area reasonably well.

6.2.2 Spatial accuracy – number of EAs/SP classified as urban

In Table 2, we pooled all EAs in 1996 and SPs in 2011 and compared their census urban categorisation against data from the night lights. These results are derived from a confusion matrix that compares which EA/SP is urban or not in both censuses and night lights data (EA/SP with at least a lit pixel).

About 77% of the EAs in 1996 and 86% of the SPs in 2011 agree with the night lights on their urban categorisation.

Table 2: Comparison of urban EA/SP from censuses and night lights – 1996 and 2011

Year	Unit of aggregation	Data source	Urban	Non-urban	Accuracy
1996	Enumeration Areas	Census	39745	54461	76.86%
		Night lights	38766	55440	
2011	Sub-places	Census	7791	14317	85.97%
		Night lights	6677	15431	

6.2.3 Urban growth

Figures 11-15 in the Appendix show changes in the urban extent based on night lights in 1996 and 2011 compared against satellite maps in early 2023 for selected South African cities: City of Johannesburg, East London, Kimberly, Kuils River and Mbombela, Paarl, Polokwane, Port Elizabeth and Uitenhage, Klerksdorp, Pietermaritzburg, and Musina.

First, Figure 4 above shows notable differences between the census urban and the DMSP-OLS urban areas of the City of Johannesburg, particularly an area in the top left corner. Figure 11 complements Figure 4 to show changes in night lights in urban areas in 1996 and in 2011. We identify the top-left corner of Figure 4 as the area around the Lanseria International Airport; the lit area has grown between 1996 and 2011. Figures 12-15 show a general increase in the lit area between 1996 and 2011 for the selected cities. The growth is not fragmented but expanded from areas already lit in 1996 to form contiguous urban areas.

Table 3 compares the size of the urban area as defined in censuses against the size derived from the night lights. The census urban definition has larger areas (3.02% in 1996 and 3.04% in 2011) than the nighttime lights (0.77% in 1996 and 0.96% in 2011) urban extent. Between 1996 and 2011, the census urban extent grew by 0.5% and the nights lights urban extent grew by 25.4%.

Results in Table 3 suggest that some administrative urban areas are not captured by the night lights or have not fully developed to illuminate significant night lights.

Table 3: Urban area size – 1996 and 2011 censuses and DMSP-OLS nighttime lights

Year	Census			DMSP-OLS nighttime lights		
	Total area (km2)	Urban area (km2)	Urban (%)	Total area (km2)	Urban area (km2)	Urban (%)
1996	1219537	36886	3.02	1219226	9346	0.77
2011	1219794	37061	3.04	1219226	11724	0.96

6.2.4 Change in brightness

Table 4 summarises the nighttime lights data for South African urban areas (DN >0) based on the deblurred images. These values are affected by variations in different sensor recording and the SOL is affected by top-coding of the DN values for urban cores like the City of Johannesburg. With that in mind, an urban area had a minimum DN threshold value of 26 in 1996 and about 18 in 2011. The average DN value dropped from 54.8 in 1996 to 48.8 in 2011. This is probably because of increasing lit areas but with low DN values and sensor variation. The SOL grew by 11.5% and the AoL grew by 25.4% between 1996 and 2011.

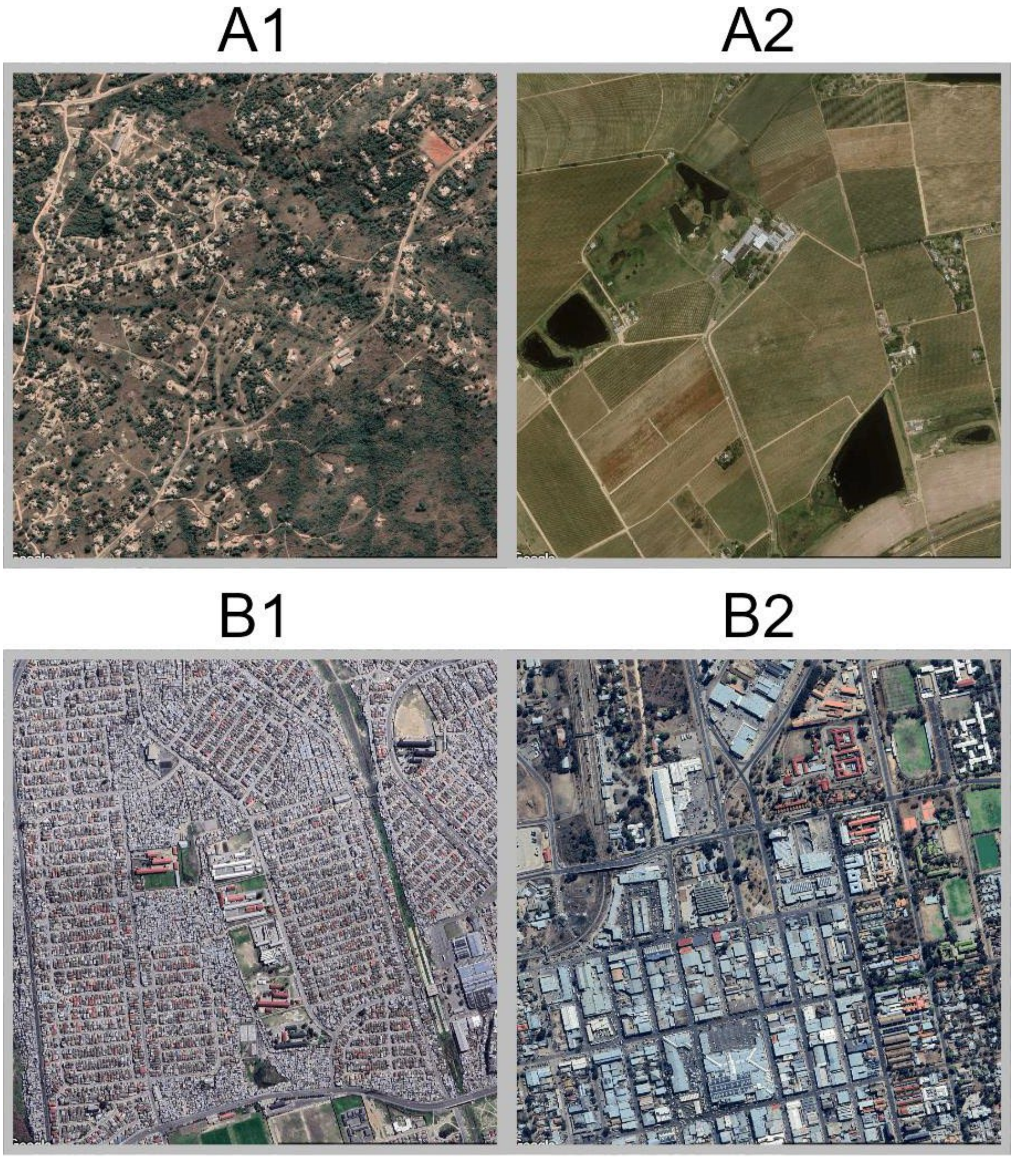
Table 4: Summary of nighttime lights data for South Africa

Year	1996	2011
Minimum	26.2	17.8
Median	61.1	56.8
Mean	54.8	48.8
Maximum	62.6	60.2
Standard deviation	11.7	14.8
SOL	594877	664113
AoL (pixels)	10806	13556

6.2.5 Low threshold vs high threshold nighttime urban areas

Figure 5 shows satellite maps of selected low urban threshold (areas with minimum DN values of 17.8) against high urban threshold (areas with maximum DN values of 60.2) areas. The top panel shows low threshold nighttime urban areas, where A1 is a rural area in the Greater Tzaneen local municipality in the Limpopo province and A2 is a farming area in Stellenbosch, Western Cape province. The bottom panel shows high threshold nighttime urban areas where B1 is a densely populated residential area in Cape Town, Western Cape province and B2 is an urban industrial area in Polokwane, Limpopo province. Different areas with different economic activities can have the same average DN value. It is difficult to tell how many structures need to be there to illuminate a certain amount of nighttime light.

Figure 5: Satellite maps of low-threshold and high-threshold nighttime urban areas



6.3 Validation

In this section, we compare the various socio-economic measures from census data against nighttime lights measures of urban extent and nighttime lights inequality. We compare these nighttime lights measures against South African census data from 1996 and 2011. First, we show the correlations between the AoL or the log-transformed AoL and the raw or log-transformed versions of the socio-economic measures. After establishing which version of the variables correlates better, we fit a linear trend. Our approach shows a scatter plot of the estimated census-based indicators against nighttime lights-based measure of lit pixels or "area of lights" for each relationship tested. In addition to the correlation coefficients, the scatter plot complements our understanding of the variation between the nightlight-based "area of lights" and the census-based measures. We also include the corresponding R2 and p-value of the linear fit.

The bivariate comparison of NTL-based "area of lights" and the various census-based indicators cannot control for other factors affecting the correlation between these measures. Our primary predictor is the "area of lights" (AoL) computed from the satellite data. In other words, we want to test if the size of lit area can predict various socio-economic measures. We provide additional results with district council/census year fixed effects to account for systematic differences between district councils and census years.

6.3.1 Correlation coefficients

Table 5 shows correlations between the AoL or the log transform, log(AoL) against census urban area size (UrbArea), urban population (UrbPop), households using electricity for lighting (Hhelec) and the proportion of households whose income per capita was below the upper bound of poverty lines (UBPL) for the respective years.

Table 5: Correlations between AoL or log(AoL) against census-derived variables

		1996		2011		Overall
variable	AoL	log(AoL)	AoL	log(AoL)	AoL	log(AoL)
UrbArea	0.142	0.197	0.509	0.346	0.129	0.161
UrbPop	0.951	0.776	0.945	0.710	0.940	0.718
Hhelec	0.957	0.784	0.951	0.756	0.918	0.727
UBPL	-0.662	-0.688	-0.555	-0.581	-0.569	-0.599
log(UrbArea)	0.380	0.500	0.480	0.431	0.367	0.427
log(UrbPop)	0.759	0.882	0.803	0.847	0.774	0.849
log(Hhelec)	0.794	0.936	0.795	0.870	0.749	0.848
log(UBPL)	0.794	0.936	0.795	0.870	0.749	0.848

AoL – night lights lit area, UrbPop – urban population, Hhelec – households using electricity for lighting, UBPL – the proportion of households with income below the upper-bound poverty line.

Generally, the untransformed AoL correlate better with the untransformed urban population (0.951 in 1996, 0.945 in 2011 and 0.94 overall) and households using electricity for lighting (0.957 in 1996, 0.951 in 2011 and 0.918 overall). Therefore, we fit the following regression model:

$$UrbPopit = \alpha + \beta * AoLit + \theta i + \eta t + \epsilon it$$

$$Hhelecit = \alpha + \beta * AoLit + \theta i + \eta t + \epsilon it$$

where i is a subscript for district council and t for year. The θi terms are district council fixed effects,

ηt year fixed effects and ϵit is an error term. For cross-sectional analysis, θi and ηt are not considered and the t falls away (such as $yi = \alpha + \beta * AoLi + \epsilon i$ where yi is any one of the outcomes) and this applies to all equations below.

The logarithm transformed AoL correlate better with the log transformed variables of the proportion of people falling below the upper bound of the poverty line (0.936 in 1996, 0.87 in 2011 and 0.848 overall) and the urban area size (0.50 in 1996, 0.431 in 2011 and 0.427 overall). As a result, we fit the following models:

$$\log(UBPLit) = \alpha + \beta * \log(AoLit) + \theta i + \eta t + \epsilon it$$

$$\log(UrbAreait) = \alpha + \beta * \log(AoLit) + \theta i + \eta t + \epsilon it$$

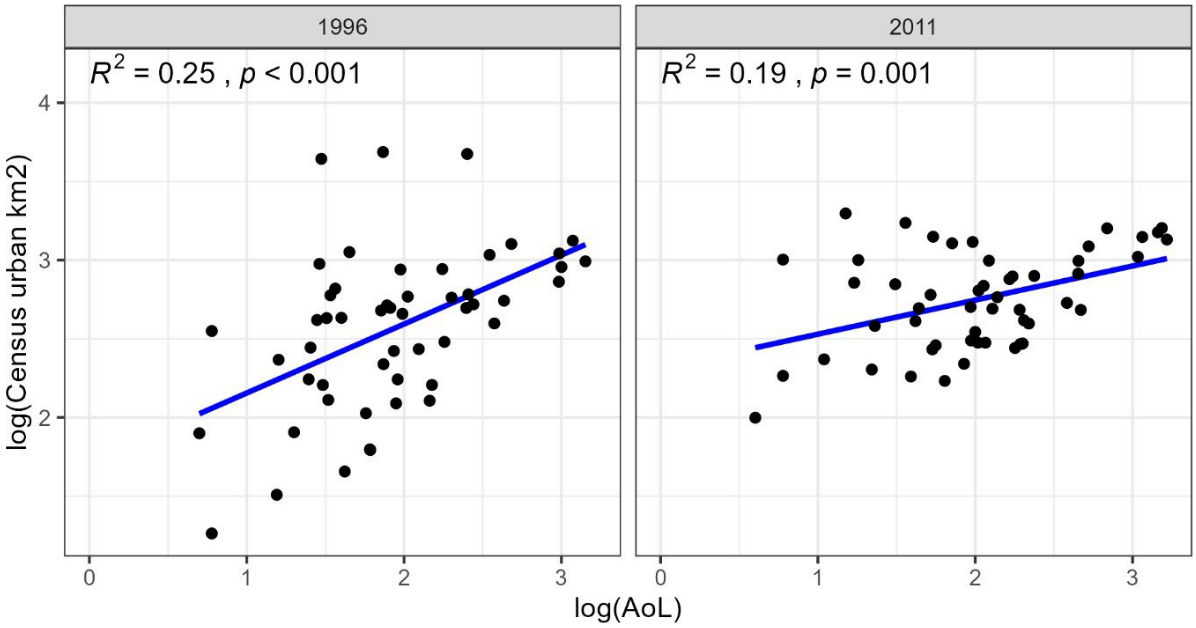
Also not shown in the table is the correlation between the household per capita income Gini coefficient and the pixel-level night lights Gini index, which is 0.23 in 1996 and 0.174 in 2011. We fit the untransformed relationships:

$$IncomeGiniit = \alpha + \beta * NightLightsGiniit + \theta i + \eta t + \epsilon it$$

6.3.2 Night lights and urban extent

Figure 6 shows the relationship between the census-based urban area size estimate and the lit night lights area.

Figure 6: Urban land (km^2) against the number of lit pixels by census year



There is a weak and significant positive relationship between the census urban size and the night lights lit areas in 1996 ($R^2 = 0.25$) and 2011 ($R^2 = 0.19$).

The regression results in Table 6 confirm that the night lights "area of lights" is a consistent predictor of designated census urban extent in both periods.

Column 3 in Table 6 shows that a one percent increase in the AoL is associated with a 0.33 percent increase in the census urban area size. This relationship remains after adding year-fixed effects and disappears after including District Council fixed effects. This suggests that the relationship between lit area and urban extent is affected by other factors that vary across district councils.

Table 6: Regression model predicting urban extent from lit pixels

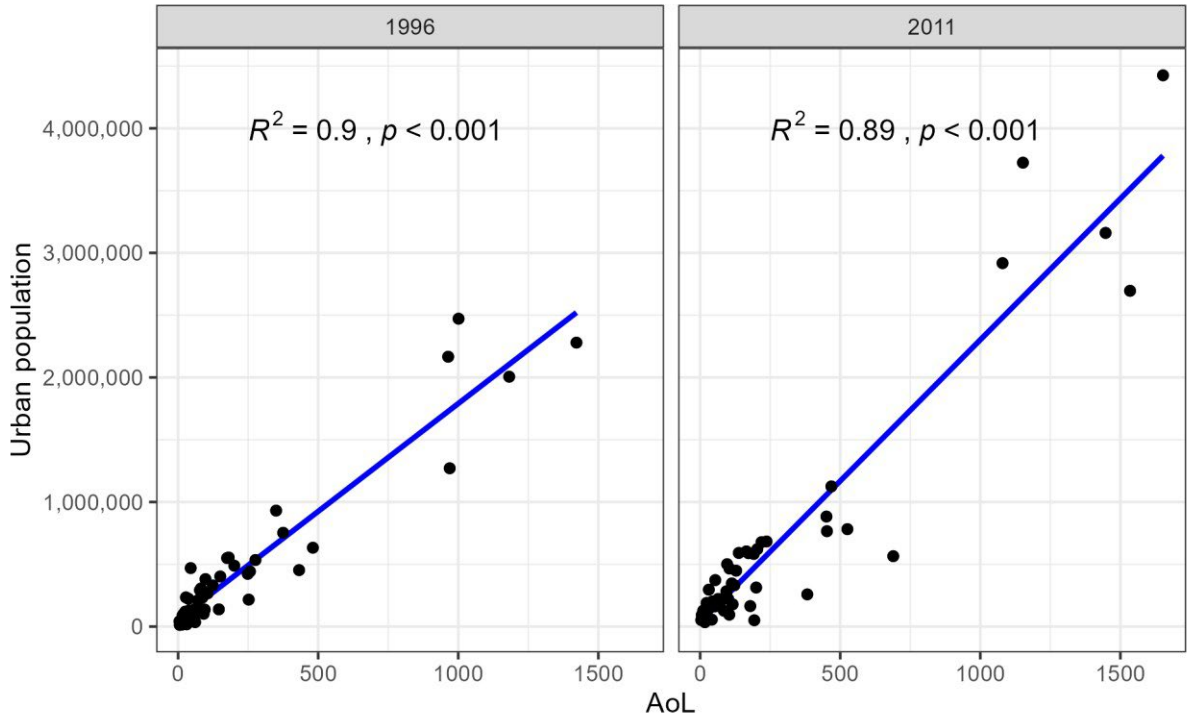
	(1)	(2)	(3)	(4)	(5)
Variables	1996	2011	Pooled	Pooled	Pooled
(Intercept)	1.717***	2.313***	2.007***	1.945***	1.863**
	(0.217)	(0.135)	(0.130)	(0.132)	(0.583)
log10(AoL)	0.438***	0.217**	0.329***	0.320***	0.393
	(0.107)	(0.064)	(0.063)	(0.062)	(0.297)
Num. Obs.	52	52	104	104	104
R2 Adj.	0.235	0.169	0.203	0.229	0.685
Year FE	No	No	No	Yes	Yes
District FE	No	No	No	No	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001; Standard errors in parentheses

6.3.3 Night lights and urban population

Figure 7 shows the relationship between the census-based estimate of the urban population and the night lights lit area.

Figure 7: Estimated urban population against the number of lit pixels by census year



There is a strong and significant positive relationship between the census urban population and the night lights lit areas in 1996 ($R^2 = 0.90$) and 2011 ($R^2 = 0.89$).

Table 7: Regression model predicting the urban population from lit pixels

	(1)	(2)	(3)	(4)	(5)
Variables	1996	2011	Pooled	Pooled	Pooled
(Intercept)	58915+	35183	38157	-8790	13223
	(30262)	(52611)	(32470)	(41130)	(162256)
AoL	1732***	2267***	2067***	2057***	2331***
	(80)	(111)	(76)	(75)	(395)
Year FE	No	No	No	Yes	Yes
District FE	No	No	No	No	Yes
Num.Obs.	52	52	104	104	104
R2 Adj.	0.902	0.891	0.879	0.882	0.92

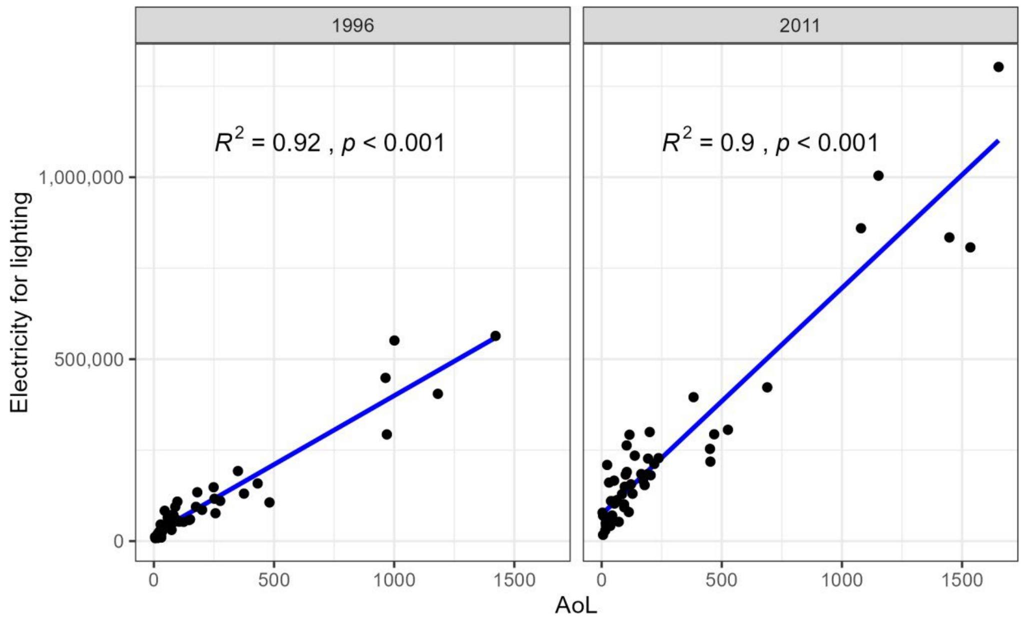
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001; Standard errors in parentheses

The regression results in Table 7 show that the night lights lit area consistently predicts the urban population across the two time periods. The lit area explains at least 88% of the variation in the urban population by the district council. A unit increase in AoL (approximately 1km x 1km) is associated with an average increase of about 2000 people in urban areas. This relationship remains after including year-fixed effects and District Council-fixed effects.

6.3.4 Night lights and electrification

Figure 8 shows the relationship between the census-based estimate of the number of households using electricity for lighting and the night lights lit area.

Figure 8: Number of households using electricity for lighting against the number of lit pixels by census year



A strong and significant positive relationship exists between the census estimate of the number of households using electricity for lighting and the night lights lit areas in 1996 (R^2 = 0.92) and 2011 (R^2= 0.9).

The regression results in Table 8 show that the night lights lit area is a strong predictor of the number of households using electricity for lighting across the two time periods. The lit area explains at least 81% of the variation in the number of households using electricity for lighting by the district council. A unit increase in AoL is associated with an average increase of about 378 and 622 households using electricity for lighting in 1996 and 2011 respectively. This relationship remains after including year- fixed effects and district council-fixed effects.

Table 8: Regression model predicting the number of households using electricity for lighting from lit pixels

	(1)	(2)	(3)	(4)	(5)
Variables	1996	2011	Pooled	Pooled	Pooled
(Intercept)	21392**	73231***	41767***	-9463	-39044
	(6194)	(13613)	(10962)	(11518)	(50461)
AoL	378***	622***	538***	527***	931***
	(16)	(29)	(25)	(21)	(123)
Year FE	No	No	No	Yes	Yes
District FE	No	No	No	No	Yes
Num. Obs.	52	52	104	104	104
R2 Adj.	0.913	0.902	0.812	0.873	0.895

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard errors in parentheses

6.3.5 Night lights and poverty

Figure 9 shows the relationship between the census-based proportion of households whose per capita income is less than the upper bound of the poverty line and the night lights lit area.

There is a significant negative relationship between poor households and the night lights lit areas both in 1996 ($R^2 = 0.46$) and 2011 ($R^2 = 0.33$).

Figure 9: Proportion of households below UBPL against number of lit pixels by census year

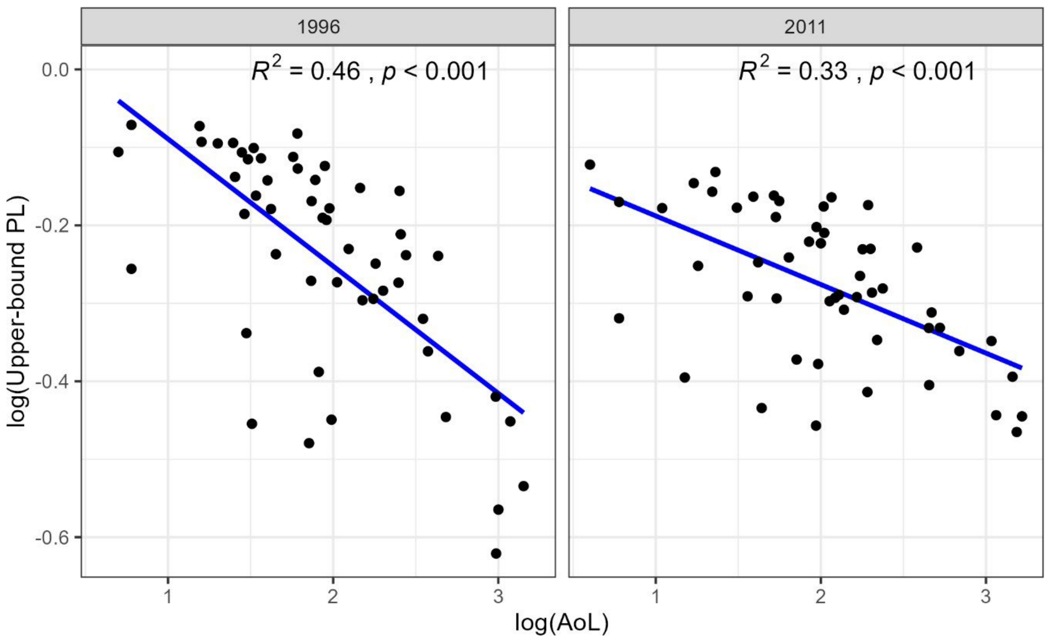


Table 9: Regression model predicting the proportion of households below the UBPL from lit pixels

	(1)	(2)	(3)	(4)	(5)
Variables	1996	2011	Pooled	Pooled	Pooled
(Intercept)	0.081*	-0.100*	0.003	0.051*	-0.282***
	(0.031)	(0.038)	(0.032)	(0.025)	(0.072)
log10(AoL)	-0.117***	-0.088***	-0.108***	-0.102***	-0.006
	(0.015)	(0.018)	(0.016)	(0.012)	(0.037)
Num. Obs.	52	52	104	104	104
R2 Adj.	0.527	0.313	0.315	0.604	0.931
Year FE	No	No	No	Yes	Yes
District FE	No	No	No	No	Yes

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard errors in parentheses

Table 9 shows that an increase in the AoL is associated with a reduction in the proportion of poor households. A one percent increase in AoL is associated with about a 13 percent decrease in the proportion of poor households for the pooled model.

6.3.6 Night lights and inequality

Figure 10 shows the relationship between household per capita income Gini against the night lights Gini index of lit pixels.

Figure 10: Household per capita income Gini against night lights Gini index

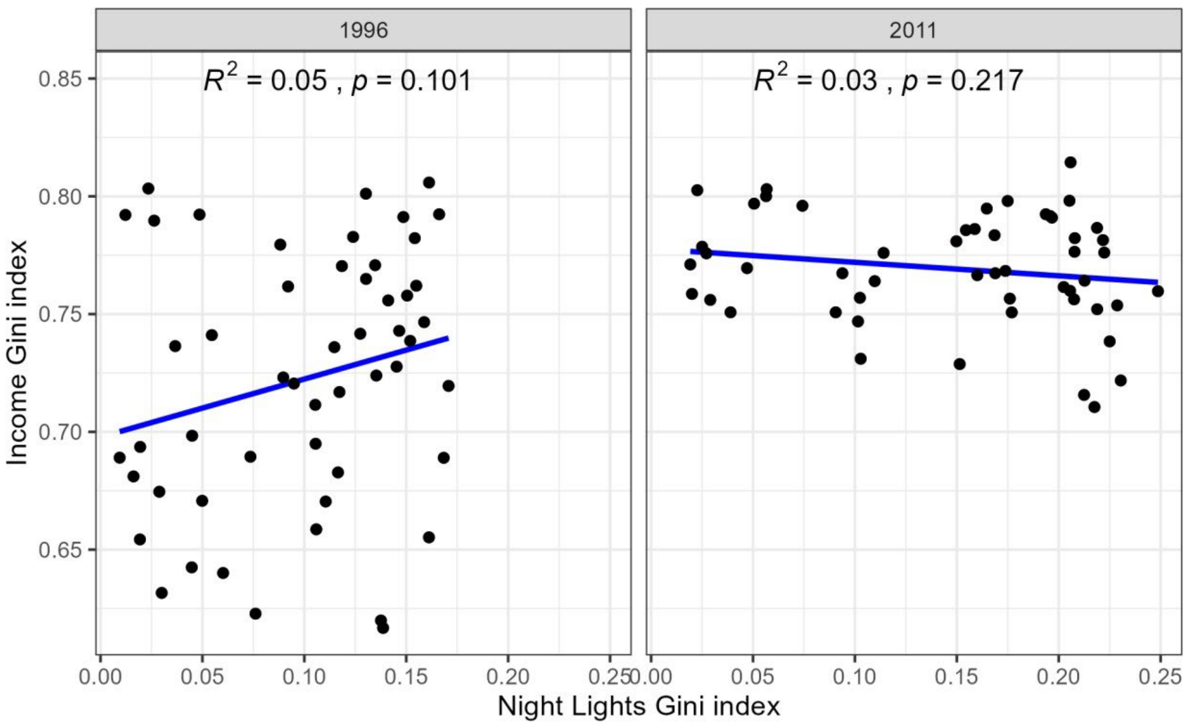


Figure 10 suggests no clear relationship exists between the income Gini and the night lights Gini. We observed a non-significant positive relationship in 1996; in 2011, the relationship was reversed and still insignificant.

Table 10: Regression model predicting household income Gini from nighttime lights Gini

	(1)	(2)	(3)	(4)	(5)
Variables	1996	2011	Pooled	Pooled	Pooled
(Intercept)	0.698***	0.778***	0.725***	0.718***	0.637***
	(0.016)	(0.007)	(0.010)	(0.009)	(0.034)
Night Lights Gini	0.246	-0.057	0.168*	0.045	0.017
	(0.147)	(0.046)	(0.070)	(0.067)	(0.166)
Year FE	No	No	No	Yes	Yes
District FE	No	No	No	No	Yes
Num.Obs.	52	52	104	104	104
R2 Adj.	0.034	0.011	0.045	0.231	0.597

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard errors in parentheses

Results in Table 10 confirm the weak and non-significant relationship between the household income based and the night lights-based Gini coefficients.

7. Discussion

This report presents an application of using the DMSP-OLS nighttime lights data to analyse the dynamics of South African urban economies over the past two and half decades. We specifically explored what the luminosity data reveal about change and variation in urban extent, urbanisation, and selected socio-economic indicators, such as poverty, inequality, and access to electricity. We compared the night lights measures against South African census data from 1996 and 2011, and this was performed at the second sub-national level, such as District Council. Boundaries have changed in district councils across censuses, and our study used boundaries from the 2011 census. Our results show a weak but significant positive relationship between South African census urban area size and lit areas derived from the night lights. We also observed a strong and significant positive relationship between the census urban population and the night lights lit areas. The estimated number of households using electricity for lighting derived from the censuses has a strong positive association with the night lights lit area. The proportion of households with a household income below the upper- bound of the poverty line is negatively associated with lit area derived from the night lights. The results show that the proportion of poor households decreases as lit area increases. There was no significant association between household income-based Gini coefficient and the night lights-based Gini coefficients.

7.1 Night lights and urban extent

In this analysis, we observed that after applying the deblurring method of Abrahams, Oram and Lozano-Gracia (2018) and the intercalibration method of Elvidge, Hsu, Baugh et al. (2014), the DMSP- OLS series DN threshold for an urban area was 26.2 in 1996 and 17.8 in 2011. First, our study confirms that these DN thresholds vary across time, probably due to sensor variation. Second, these threshold DN values are higher than the 13 suggested by Small, Elvidge, Balk et al. (2011) and lower than the 30 used by others (e.g., Sutton et al., 2007).

There are several reasons why there is no strong relationship between the census urban area and the night lights lit area. South Africa's history of segregation makes the definition of "urban" or "non- urban" a complex process. The Apartheid-era policy of separate development created major discontinuities in spatial development (Baffi, Turok and Vacchiani-Marcuzzo, 2018; Giraut and Vacchiani-Marcuzzo, 2009). The census definition of "urban" was based on official demarcations of South Africa into different settlement types: urban formal, urban informal (informal settlements often found on the peri-urban fringes), former homeland areas (territories set aside for Black South Africans) and commercial agriculture areas. The former homelands form a "rural-urban continuum" that includes formal "dormitory townships or dense rural settlements, small towns, agricultural villages, and small farms" (Atkinson, 2014: 5). In these homelands, villages are usually regarded as "rural" whereas bigger towns were reclassified as "urban". After apartheid, areas benefited from massive rural electrification programmes (Bekker et al., 2008). The 2001 census definition of an urban area used for the 1996 comparison is based on spatial form and land use (Statistics South Africa, 2003b), not electricity access. Therefore, using the perimeter of lit areas derived from night lights to proxy for an urban area will likely not match the census urban/non-urban demarcations for some areas. This is because some places have access to electricity and possibly illuminate light at night but are not defined as urban areas. The urban/non-urban classification is also defined at the EA/SP level. However, there are some urban EAs/SPs covering areas like national parks (e.g., Table Mountain in Cape Town) and such places do not illuminate night lights. As a result, there is going to be some disagreement between the official urban classification and the night lights lit areas.

7.2 Night lights and urban population and electrification

There is a high correlation between the night lights lit area and the census urban population. The night lights lit areas explain about 90% of the variation in the urban population by district council. The high correlation between night lights lit areas and urban population is consistent with results observed elsewhere (Elvidge, Baugh, Kihn et al., 1997c). This relationship is consistent in 1996 and 2011, and even in the pooled model controlling for year and district council fixed effects. Unlike the urban area size discussed above, the night lights lit area measure correlates better with the urban population because this is the same population responsible for the light emissions. The proportion of South African households using electricity for lighting was 58.2% in 1996 and 84.7% in 2011 (Statistics South Africa, 2011a). The high proportion of households using electricity for lighting correlates strongly with the night lights lit area for the district councils (R2 of at least 0.90). The high correlation between the night lights and both the urban population and electricity access is expected since the night lights by their definition, identify urban areas and human settlements by their night lights emissions.

7.3 Night lights and poverty and inequality

We observed a significant negative relationship between poor households and the night lights lit areas both in 1996 ($R^2 = 0.54$) and 2011 ($R^2 = 0.33$). Subash et al. (2018) also demonstrate this relationship pattern between night light DN values and poverty rates in Indian states. This suggests that lit areas are less likely to have poor households. On the strength of the relationship, Dugoua, Kennedy and Urpelainen (2018) found that the sum of lights did not perform well at measuring poverty for the Indian villages data that they analysed. We found no significant correlation between the household income Gini and night lights Gini. Previous studies also observed a non-significant relationship

(Weidmann and Theunissen, 2021). We derived the Gini coefficient from lit pixels in urban areas and cities. A potential problem with this approach is that night lights from urban areas reflect the provision of public services rather than household socio-economic status. This is possibly one of the reasons why we observe a weak relationship between lit area and poverty rates and no association between the night lights Gini index and the household income Gini coefficient.

7.4 Limitations

There were several limitations in our study. The South African sub-national geography boundaries keep changing, making comparing changes over time difficult. Our study attempted to remedy this by re-apportioning each census EAs to district council boundaries. While this is not a perfect solution, re- apportioning small units is unlikely to cause major biases when aggregated at the district council level. Another limitation was the inconsistent definition of urban areas across censuses. This is a broad problem for South African geography and there is a need for a unified definition of urban/non-urban. We could not compare the night lights against data from the 2001 census because a key variable identifying urban areas was unavailable from the community profiles. This deprived us of the opportunity to explore and understand the various relationships in 2001. The EA geography type, urban or non-urban, that we aggregated to the district council level was only available in the censuses up to 2011. We could not explore the performance of the superior VIIRS-DNB night lights available from 2012 onwards against the various measures considered in this study.

7.5 Potential use of nighttime lights

We have highlighted several known limitations inherent in the DMSP-OLS night lights used in this study. Despite these limitations, some studies are optimistic about applying the DSMSP-OLS data as a proxy for cases with limited or no relevant data. We could not compare South African survey data with the improved NPP-VIIRS night lights products. Studies applying the NPP-VIIRS night lights products have highlighted their great potential to proxy for several measures, including those assessed in this study. Shi et al. (2014) observed that the VIIRS data are better for mapping urban extent compared to the DMSP-OLS for 12 cities in China. They attribute this improvement to the high spatial resolution and wide radiometric detection range of NPP-VIIRS data. Xie et al. (2014) found that NPP-VIIRS imagery more effectively characterised urban spatial variation than the DMSP-OLS for US counties. The same study also found that the correlation between the urban population and each of DMSP-OLS and NPP-VIIRS was almost the same, but the latter had a higher correlation to the urban population density at the county level. Li et al. (2013) found that the NPP-VIIRS had better explanatory power than the DMSP-OLS in predicting China's gross regional product (GRP) at the provincial and county level. Shi, Huang, Yu et al. (2014) observed that the NPP-VIIRS correlated better with socio-economic indicators such as education, income, and Gini coefficient than DMSP-OLS for 12 Chinese cities. For electrification, the NASA Black Marble nighttime light data, a high-quality nightlight product derived from NPP-VIIRS, have been applied in near-real time to monitor disaster-related power outages and recovery (Wang et al., 2018; Román et al., 2019). Yu et al. (2015) demonstrated that the NPP-VIIRS data can be useful for assessing poverty at the county level in China. Therefore, improved nightlight products show great potential to measure socio-economic measures and urban dynamics.

8. Conclusions

There is a weak association between the DMSP-OLS night lights lit area and South African administrative urban extent. This is probably because of South Africa’s unusual urbanisation process that was inherited from apartheid-era spatial engineering policies. There is no consistent urban or city system such that some dense rural settlements that emit night lights are administratively identified as rural areas. The lit area measure performs well at predicting the urban population and the number of households using electricity for lighting at the district level. This association is expected because the night lights identify footprints of human presents and activities. The night lights performed poorly at predicting poverty rates and inequality. The probable explanation is that night lights from urban areas reflect the provision of public services than household socio-economic status. Therefore, the night lights are not good at measuring some of these socio-economic variables.

9. Recommendations

We recommend replicating this study, comparing the 2022 South African census results against the superior VIIRS-DNB night lights data. This would help to evaluate the usefulness of the VIIRS-DNB data using detailed census data. We observed some mismatches between the census urban and night lights lit area. Among, for example, EAs and SPs that did not match, can the night lights identify informal settlements and how they have evolved? This helps to identify marginalised populations.

References

Abrahams, A., C. Oram and N. Lozano-Gracia. 2018. "Deblurring DMSP nighttime lights: A new method using Gaussian filters and frequencies of illumination", Remote Sensing of Environment 210:242-258.

Addison, D.M. and B. Stewart. 2015. "Nighttime lights revisited: the use of nighttime lights data as a proxy for economic variables", World Bank Policy Research Working Paper (7496)

Amaral, S., G. Câmara, A.M.V. Monteiro et al. 2005. "Estimating population and energy consumption in Brazilian Amazonia using DMSP night-time satellite data", Computers, Environment and Urban Systems 29(2): 179-195.

Atkinson, D. 2014. "Rural-urban linkages: South Africa case study", Territorial Cohesion for Development Program, Rimisp, Santiago.

Baffi, S., I. Turok and C. Vacchiani-Marcuzzo. 2018. "The South African urban system," in International and transnational perspectives on urban systems. Springer, pp. 285-314.

Bekker, B., C. Gaunt, A. Eberhard et al. 2008. "Uncertainties within South Africa's goal of universal access to electricity by 2012", Journal of Energy in Southern Africa 19(2):4-13.

Bickenbach, F., E. Bode, P. Nunnenkamp et al. 2016. "Night lights and regional GDP", 152:425-447.

Bluhm, R. and M. Krause. 2022. "Top Lights: Bright cities and their contribution to economic development", Journal of Development Economics 157: 102880.

Cao, X., Y. Hu, X. Zhu et al. 2019. "A simple self-adjusting model for correcting the blooming effects in DMSP-OLS nighttime light images", Remote Sensing of Environment 224:401-411.

Chen, X. and W.D. Nordhaus. 2011. "Using luminosity data as a proxy for economic statistics", Proceedings of the National Academy of Sciences 108(21):8589-8594.

Croft, T.A. 1978. "Nighttime images of the earth from space", Scientific American 239(1):86-101. Doll, C.N. 2008. "CIESIN thematic guide to night-time light remote sensing and its applications", Center for International Earth Science Information Network of Columbia University, Palisades, NY.

Dugoua, E., R. Kennedy and J. Urpelainen. 2018. "Satellite data for the social sciences: measuring rural electrification with night-time lights", International Journal of Remote Sensing 39(9):2690-2701.

Elvidge, C., K. Baugh, V. Hobson et al. 1997a. "Satellite inventory of human settlements using nocturnal radiation emissions: a contribution for the global toolchest", Global Change Biology 3(5):387-395.

Elvidge, C.D., K. Baugh, M. Zhizhin et al. 2017. "VIIRS night-time lights", International Journal of Remote Sensing 38(21):5860-5879.

Elvidge, C.D., K.E. Baugh, S.J. Anderson et al. 2012. "The Night Light Development Index (NLDI): a spatially explicit measure of human development from satellite data", Social Geography 7(1):23-35.

Elvidge, C.D., K.E. Baugh, E.A. Kihn et al. 1997b. "Mapping city lights with nighttime data from the DMSP Operational Linescan System", Photogrammetric Engineering and Remote Sensing 63(6):727-734.

Elvidge, C.D., K.E. Baugh, E.A. Kihn et al. 1997c. "Relation between satellite observed visible-near infrared emissions, population, economic activity and electric power consumption", International Journal of Remote Sensing 18(6):1373-1379.

Elvidge, C.D., K.E. Baugh, M. Zhizhin et al. 2013. "Why VIIRS data are superior to DMSP for mapping nighttime lights", Proceedings of the Asia-Pacific Advanced Network 35(0):62.

Elvidge, C.D., F.-C. Hsu, K.E. Baugh et al. 2014. "National trends in satellite-observed lighting: 1992- 2012," in Weng, Q (ed). Global urban monitoring and assessment through earth observation. Vol. 23. pp. 97-118.

Elvidge, C.D., H.W. Kroehl, E.A. Kihn et al. 1996. "Algorithm for the retrieval of fire pixels from DMSP operational linescan system data", Biomass burning and global change: Remote sensing, modeling and inventory development, and biomass burning in Africa 1:73-85.

Elvidge, C.D., M. Zhizhin, T. Ghosh et al. 2021. "Annual time series of global VIIRS nighttime lights derived from monthly averages: 2012 to 2019", Remote Sensing 13(5):922.

Elvidge, C.D., D. Ziskin, K.E. Baugh et al. 2009. "A fifteen year record of global natural gas flaring derived from satellite data", Energies 2(3):595-622.

Gibson, J. 2021. "Better night lights data, for longer", Oxford Bulletin of Economics and Statistics 83(3):770-791.

Gibson, J., S. Olivia, G. Boe-Gibson et al. 2021. "Which night lights data should we use in economics, and where?", Journal of Development Economics 149:102602.

Gibson, J., S. Olivia and G. Boe - Gibson. 2020. "Night lights in economics: Sources and uses 1", Journal of Economic Surveys 34(5):955-980.

Giraut, F. and C. Vacchiani-Marcuzzo (2009) Paris: IRD éditions, CD Rom.

Hao, R., D. Yu, Y. Sun et al. 2015. "Integrating multiple source data to enhance variation and weaken the blooming effect of DMSP-OLS light", Remote Sensing 7(2):1422-1440.

Henderson, J.V., A. Storeygard and D.N.J.A.e.r. Weil. 2012. "Measuring economic growth from outer space", 102(2):994-1028.

Huang, Q., X. Yang, B. Gao et al. 2014. "Application of DMSP/OLS nighttime light images: A meta- analysis and a systematic literature review", Remote Sensing 6(8):6844-6866.

Imhoff, M.L., W.T. Lawrence, D.C. Stutzer et al. 1997. "A technique for using composite DMSP/OLS "city lights" satellite data to map urban area", Remote Sensing of Environment 61(3):361- 370.

Keola, S., M. Andersson and O.J.W.D. Hall. 2015. "Monitoring economic development from space: using nighttime light and land cover data to measure economic growth", 66:322-334.

Kleynhans, E.P. and C.E. Coetzee. 2021. "The rank-size distribution of cities in South Africa", GeoJournal:1-16.

Kroth, V., V. Larcinese and J. Wehner. 2016. "A better life for all? Democratisation and electrification in post-apartheid South Africa", The Journal of Politics 78(3):774-791.

Lehohla, P.J. 2008. Measuring poverty in South Africa: methodological report on the development of the poverty lines for statistical reporting. Pretoria: Statistics South Africa.

Levin, N., C.C. Kyba, Q. Zhang et al. 2020. "Remote sensing of night lights: A review and an outlook for the future", Remote Sensing of Environment 237:111443.

Li, X., H. Xu, X. Chen et al. 2013. "Potential of NPP-VIIRS nighttime light imagery for modeling the regional economy of China", Remote Sensing 5(6):3057-3081.

Liu, Z., C. He, Q. Zhang 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): 62-72.

Lu, D., H. Tian, G. Zhou et al. 2008. "Regional mapping of human settlements in south-eastern China with multisensor remotely sensed data", Remote Sensing of Environment 112(9):3668-3679.

Lu, L., Q. Weng, Y. Xie et al. 2019. "An assessment of global electric power consumption using the Defense Meteorological Satellite Program-Operational Linescan System nighttime light imagery", Energy 189:116351.

Machemedze, T., T. Dinkelman, M. Collinson et al. 2017. "Throwing light on rural development: using nightlight data to map rural electrification in South Africa", A DataFirst Technical Paper 38.

Min, B. and K.M. Gaba. 2014. "Tracking electrification in Vietnam using nighttime lights", Remote Sensing 6(10):9511-9529.

Min, B., K.M. Gaba, O.F. Sarr et al. 2013. "Detection of rural electrification in Africa using DMSP-OLS night lights imagery", International Journal of Remote Sensing 34(22):8118-8141.

Mirza, M.U., C. Xu, B.v. Bavel et al. 2021. "Global inequality remotely sensed", Proceedings of the National Academy of Sciences 118(18): e1919913118.

Mukherjee, S., S. Srivastav, P.K. Gupta et al. 2017. "An Algorithm for Inter-calibration of Time-Series DMSP/OLS Night-Time Light Images", Proceedings of the National Academy of Sciences, India Section A: Physical Sciences 87(4):721-731.

Mveyange, A. 2018. "Measuring and Explaining Patterns of Spatial Income Inequality from Outer Space: Evidence from Africa", World Bank Policy Research Working Paper (8484).

Pfeifer, G., F. Wahl and M. Marczak. 2018. "Illuminating the world cup effect: night lights evidence from South Africa", Journal of regional science 58(5):887-920.

Roberts, M., B. Stewart, M. Prakash et al. 2015. "Global night time lights urban extents and growth patterns product", Alpha Version World Bank.

Rogan, M. and J. Reynolds. 2019. "Trends in the working poverty rate (WPR) in post-apartheid South Africa, 1997–2012", Development Southern Africa 36(5):699-715.

Román, M.O., E.C. Stokes, R. Shrestha et al. 2019. "Satellite-based assessment of electricity restoration efforts in Puerto Rico after Hurricane Maria", PloS one 14(6):e0218883.

Sahoo, S., P.K. Gupta and S. Srivastav. 2020. "Comparative analysis between VIIRS-DNB and DMSP- OLS night-time light data to estimate electric power consumption in Uttar Pradesh, India", International Journal of Remote Sensing 41(7):2565-2580.

Shi, K., C. Huang, B. Yu et al. 2014. "Evaluation of NPP-VIIRS night-time light composite data for extracting built-up urban areas", IEEE Journal of Selected Topics in Applied Earth Observations 5(4):358-366.

Small, C., C.D. Elvidge, D. Balk et al. 2011. "Spatial scaling of stable night lights", Remote Sensing of Environment 115(2):269-280.

Small, C., F. Pozzi and C.D. Elvidge. 2005. "Spatial analysis of global urban extent from DMSP-OLS night lights", Remote Sensing of Environment 96(3-4):277-291.

Statistics South Africa. 2003a. Census 2001: Concepts and definitions. Pretoria: Statistics South Africa.

Statistics South Africa. 2003b. Census 2001: Investigation into appropriate definitions of urban and rural areas for South Africa: Discussion Document. Pretoria: Statistics South Africa.

Statistics South Africa (2011a) Statistics South Africa, Pretoria.
Statistics South Africa. 2011b. Census 2011: Metadata Concepts and definitions. Pretoria: Statistics South Africa.

Statistics South Africa. 2019. National Poverty Lines: Statistical release P0310.1. Pretoria: Statistics South Africa.

Subash, S.P., R.R. Kumar and K.S. Aditya. 2018. "Satellite data and machine learning tools for predicting poverty in rural India", Agricultural economics research review 31(347-2019- 571):231-240.

Sutton, P., D. Roberts, C. Elvidge et al. 2001. "Census from Heaven: An estimate of the global human population using night-time satellite imagery", International Journal of Remote Sensing 22(16):3061-3076.

Sutton, P.C. and R.J.E.e. Costanza. 2002. "Global estimates of market and non-market values derived from nighttime satellite imagery, land cover, and ecosystem service valuation", 41(3):509- 527.

Sutton, P.C., C.D. Elvidge and T. Ghosh. 2007. "Estimation of gross domestic product at sub-national scales using nighttime satellite imagery", International Journal of Ecological Economics & Statistics 8(S07):5-21.

Thom, C. 2000. "Use of grid electricity by rural households in South Africa", Energy for Sustainable Development 4(4):36-43.

Townsend, A.C. and D.A. Bruce. 2010. "The use of night-time lights satellite imagery as a measure of Australia's regional electricity consumption and population distribution", International Journal of Remote Sensing 31(16):4459-4480.

Tuttle, B.T., S.J. Anderson, P.C. Sutton et al. 2013. "It used to be dark here: Geolocation Calibration of the Defense Meteorological Satellite Program Operational Linescan System", Photogrammetric Engineering & Remote Sensing 79(3):287-297.

UN IEAG. 2014. A world that counts–Mobilising the data revolution for sustainable development. Independent Expert Advisory Group on a Data Revolution for Sustainable Development.

United Nations. 2015. Transforming our world: The 2030 agenda for sustainable development. United Nations. 2020. Sustainable development goals.

Wang, W., H. Cheng and L. Zhang. 2012. "Poverty assessment using DMSP/OLS night-time light satellite imagery at a provincial scale in China", Advances in Space Research 49(8):1253- 1264.

Wang, Z., M. Román, Q. Sun et al. 2018. "Monitoring disaster-related power outages using NASA black marble nighttime light product", Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci 2018:1853-1856.

Wei, Y., H. Liu, W. Song et al. 2014. "Normalisation of time series DMSP-OLS nighttime light images for urban growth analysis with pseudo invariant features", Landscape and Urban Planning 128:1-13.

Weidmann, N.B. and G. Theunissen. 2021. "Estimating Local Inequality from Nighttime Lights", Remote Sensing 13(22):4624.

Wu, J., S. He, J. Peng et al. 2013. "Intercalibration of DMSP-OLS night-time light data by the invariant region method", International Journal of Remote Sensing 34(20):7356-7368.

Xie, Y., Q. Weng and A. Weng. 2014. "A comparative study of NPP-VIIRS and DMSP-OLS nighttime light imagery for derivation of urban demographic metrics," Paper presented at 2014 Third International Workshop on Earth Observation and Remote Sensing Applications (EORSA). IEEE. 335-339.

Yu, B., K. Shi, Y. Hu et al. 2015. "Poverty evaluation using NPP-VIIRS nighttime light composite data at the county level in China", IEEE Journal of Selected Topics in Applied Earth Observations Remote Sensing 8(3):1217-1229.

Zhang, Q., B. Pandey and K.C. Seto. 2016. "A robust method to generate a consistent time series from DMSP/OLS nighttime light data", IEEE Transactions on Geoscience and Remote Sensing 54(10):5821-5831.

Appendix

Figure 11: Changes in urban extent based on nightlights compared against satellite maps: City of Johannesburg

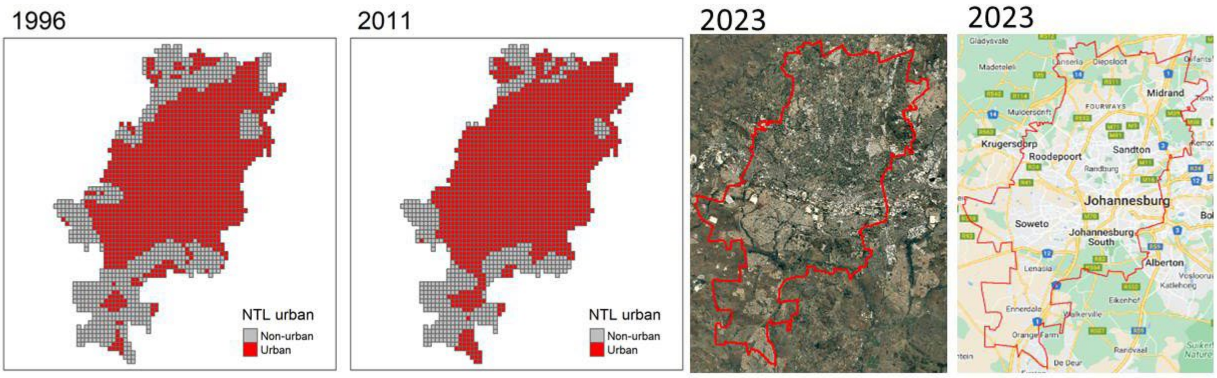


Figure 12: Changes in urban extent based on nighlights compared against satellite maps: East London, Kimberly and Kuils River.

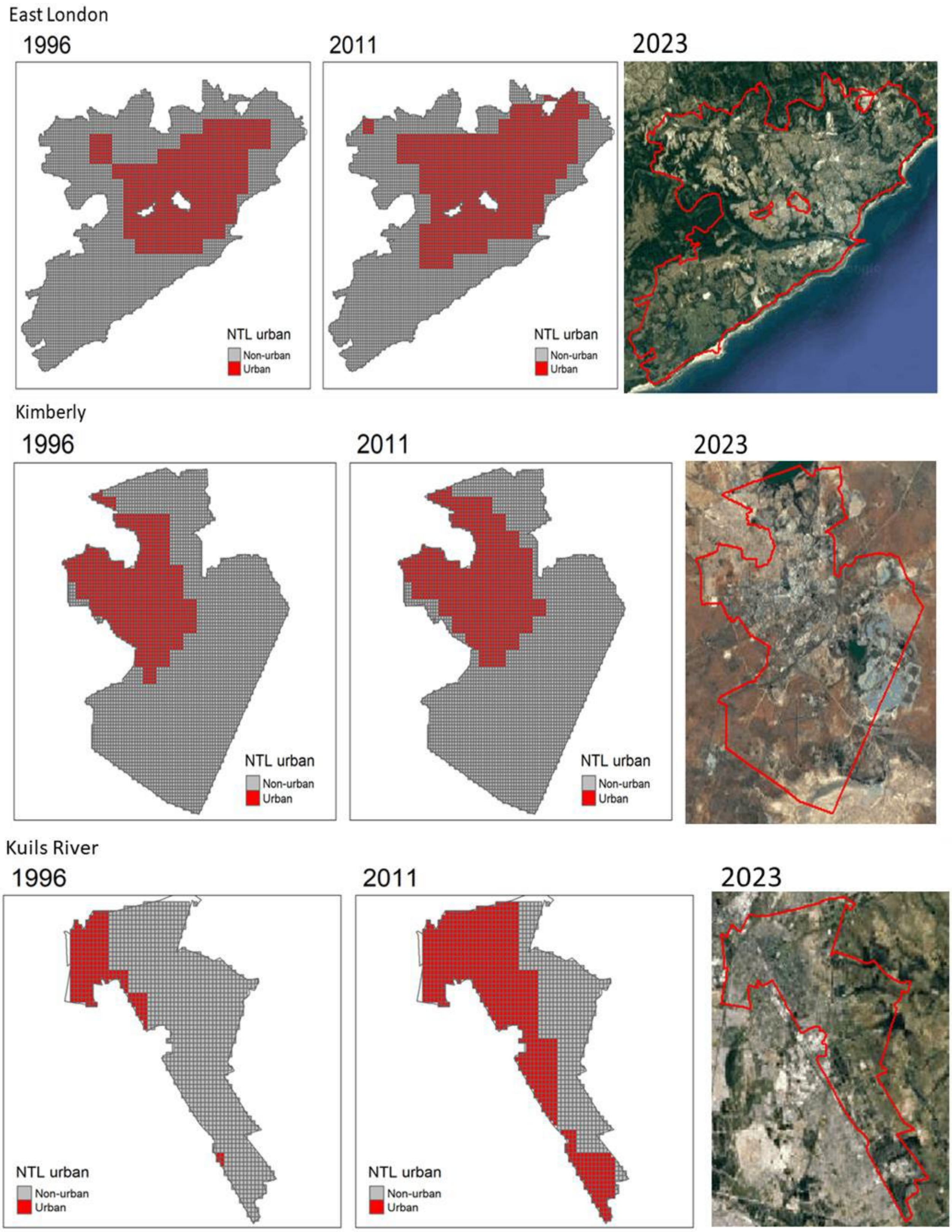


Figure 13: Changes in urban extent based on nighlights compared against satellite maps: Mbombela, Paarl and Polokwane.

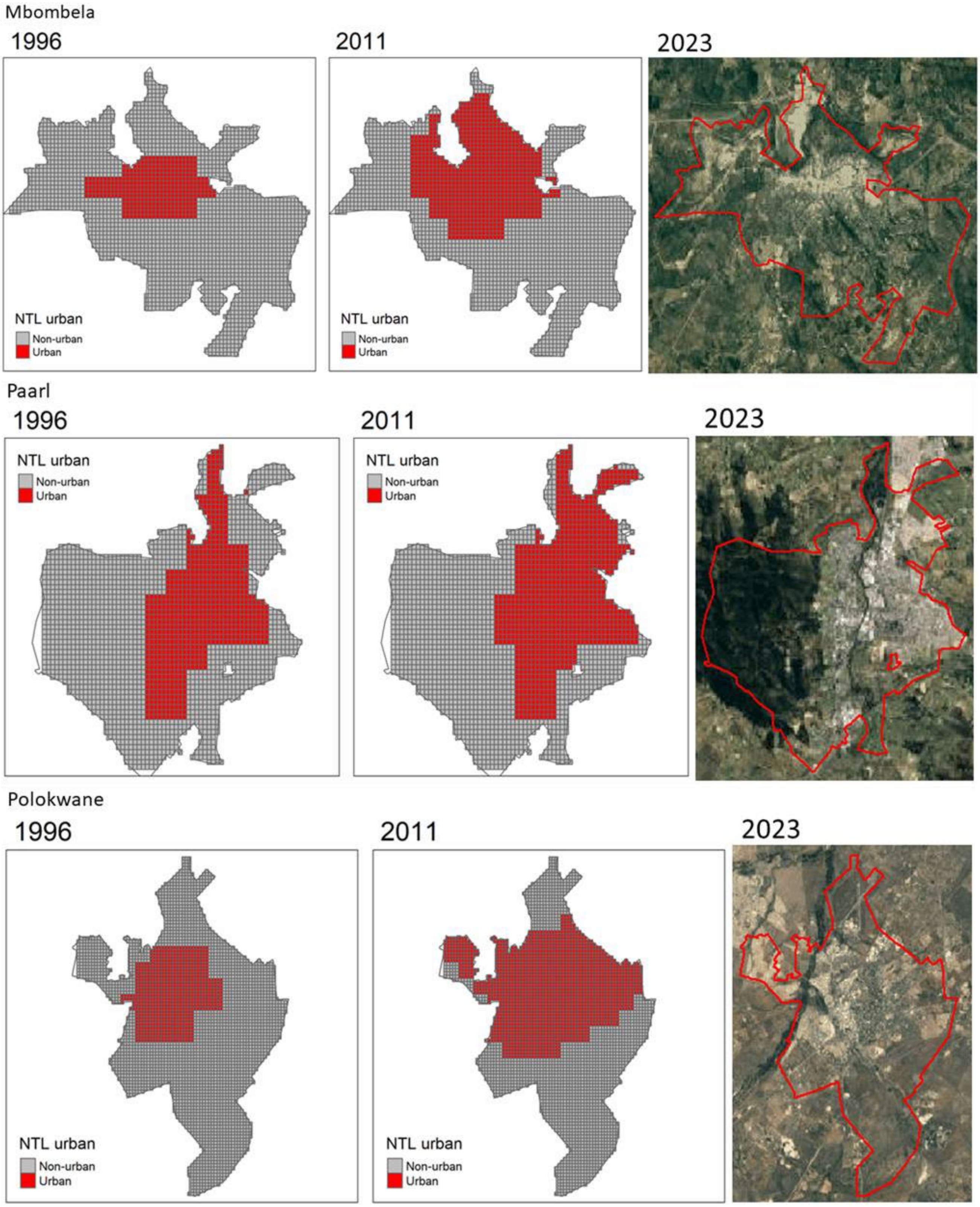


Figure 14: Changes in urban extent based on nighlights compared against satellite maps: Port Elizaberth, Uitenhage and Klerksdorp.

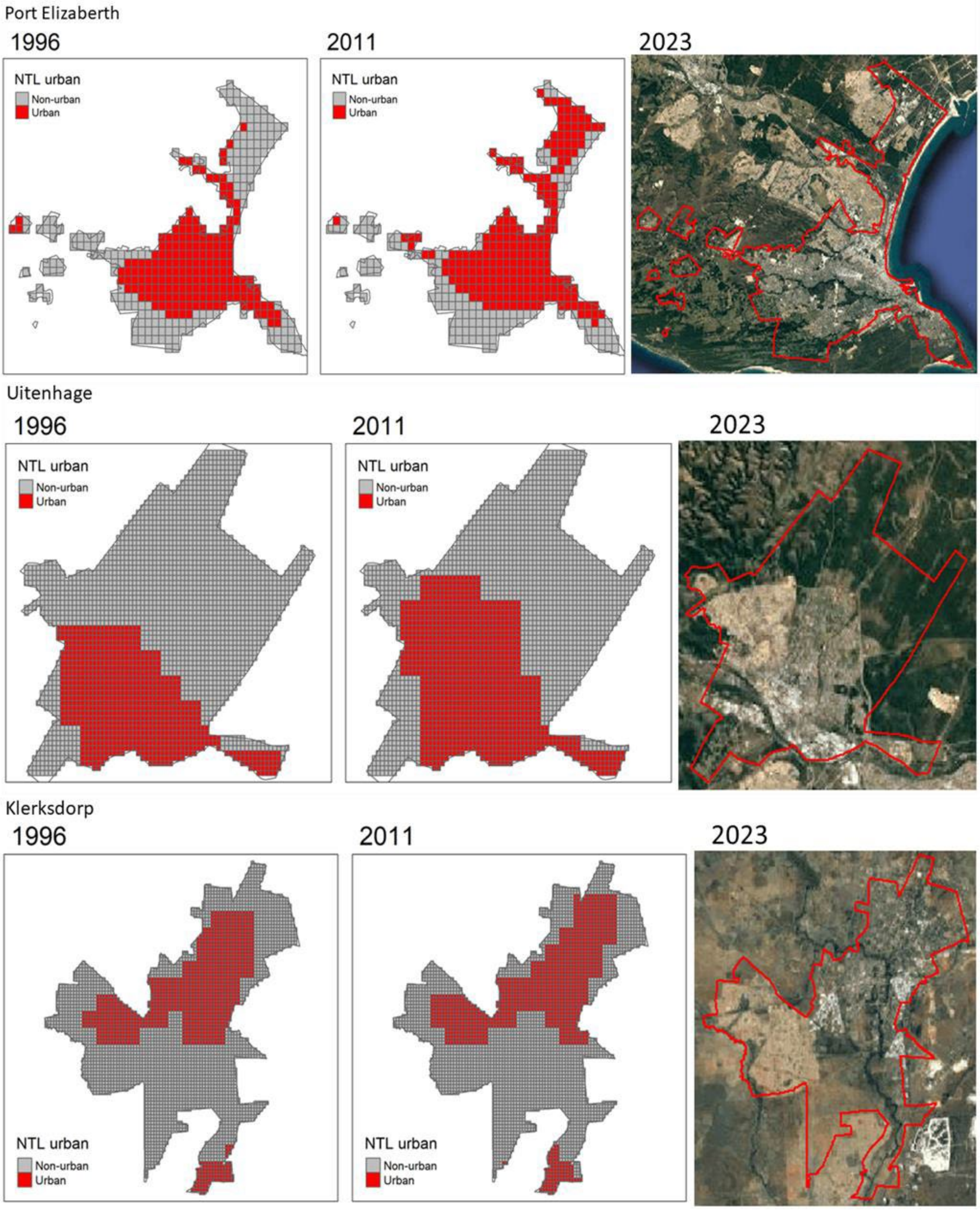
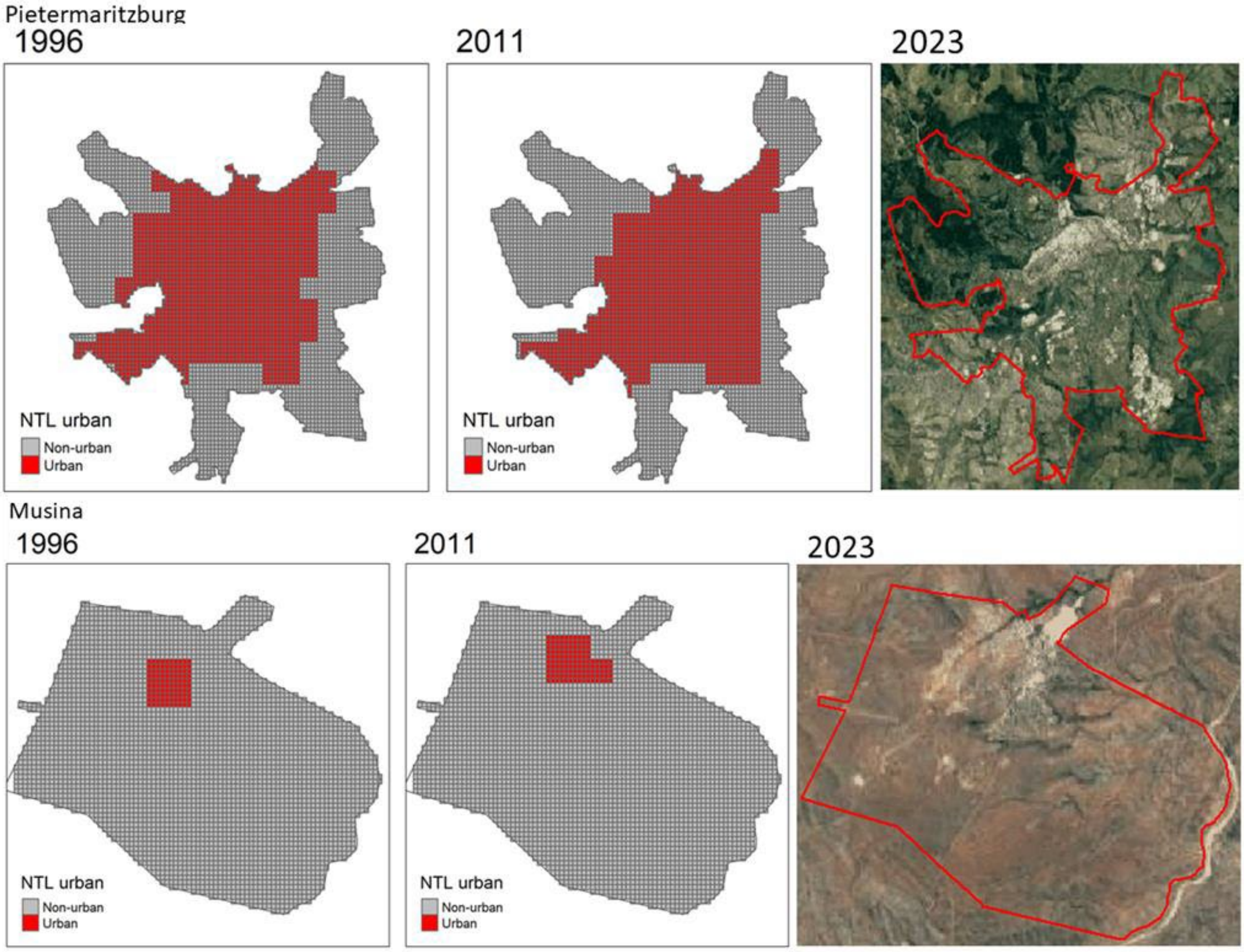


Figure 15: Changes in urban extent based on nighlights compared against satellite maps: Pietermaritzburg and Musina



Economic Research Southern Africa (ERSA) is a platform that supports the development of economic policy by connecting economic research to national policy debate and identifying areas of future research. It has served as the premier platform for economics researchers across Southern Africa to publish their work, participate in conferences and training programmes, and contribute to the national debate on public policy, since 2004. It does this by:

- Conducting on-going research that develops and contributes to research across five broad themes.
- Sharing and promoting policy relevant economic research and code through the SAMNet Initiative.
- Stimulating discussions that contribute towards national debate, by bringing a network of economic experts to share ideas.
- Upskilling academics and students through the skills development initiative.
- Nurturing economic talent by encouraging all brains that are curious about economics to grow their knowledge and confidence in the subject.

Our network draws a broad and representative range of expert economic researchers and policy makers from a variety of academic, financial and government institutions. In this way, ERSA encourages the creation, dissemination and discussion of independent and expert economic policy-oriented research.

For more information about ERSA, please visit our website at www.econrsa.org.

Other Discussion Document Publications:

Discussion Document 06: A systematic and historical review of basic income support programs in middle-income countries by Biniam Bedasso and Ermias Woldensenbet

Discussion Document 07: South Africa's yield curve conundrum by Ruan Erasmus and Daan Steenkamp

Discussion Document 08: Importance of employment programs for the youth in South Africa by Jessica Gagete-Miranda and Michelle Please

Discussion Document 09: Crime: A policy-oriented survey by Sebastian Galiani