ESTIMATING THE LEVEL OF ECONOMIC ACTIVITIES IN BOTSWANA THROUGH NIGHT LIGHT DATA

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Acknowledgements

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List of Abbreviations

BCL	Bamangwato Concessions Limited
CAGR	Cumulative Average Growth Rate
CAR	Centre for Applied Research
DMSP	Defence Meteorological Satellite Program
DNB	Day/Night Band
GDP	Gross Domestic Product
GIFOV	Ground Instantaneous Field of View
HDI	Human Development Index
IMF	International Monetary Fund
NASA	National Aeronautics and Space Administration
NL	Night Lights
NLDI	Night Light Development Index
NMGDP	Non-mining GDP
NOAA	National Oceanic and Atmospheric Administration
NPI	Normalized Poverty Index
NSL	Night-time Stable Light
OLS	Operational Linescan System
PAs	Protected Areas
SB	Statistics Botswana
SNA	System of National Accounts
SSPP	Suomi Solar Polar Partnership
US	United States
VIIRS	Visible Infrared Imaging Radiometer Suite

1 Introduction

An emerging area of economic research is the use of 'nightlights' (NL) data to complement existing economic data and provide additional insight into the level of and changes in economic activity. Nightlights data are generated by satellites scanning the earth's surface at regular intervals; the entire surface of the earth is scanned at least twice daily. The satellites record light emitted at the earth's surface, and the data are made publicly available by National Aeronautics and Space Administration (NASA). The NL data include all forms of luminescence, including electric lights, fires, lightning, reflected moonlight etc. However, the data can be cleaned to focus on electric light only, and this cleaned nightlights data has been found to be a good indicator of the level of economic activity, and changes therein: the amount of light emitted from electrical sources is closely correlated to economic activity. Nightlight data are particularly useful where formal economic activity data are weak, or infrequent, especially in low-resource countries. They can also be applied at a level of disaggregation (e.g. at a regional or district level) that conventional data may not address.

The overall objective of this study is to use nightlight intensity to track economic activity in Botswana, and in particular to track economic activity at a geographically disaggregated level. This is important because data on Gross Domestic Product (GDP) are only available at a national level and are not produced at the regional level; hence rates of economic growth in different regions of the country cannot be tracked. A recent example of where this is a problem relates to Selebi-Phikwe and the closure of the large BCL copper-nickel mine in October 2016; while the impact of the BCL closure can be tracked at a national level (the impact on Botswana's GDP and exports), the impact on Selebi-Phikwe and the surrounding areas cannot be measured using current GDP statistics.

The study addresses the following issues:

- Identifying how well the national GDP data (or alternatively non-mining GDP (NMGDP) data) for Botswana are correlated with economic activity as measured by the nightlight data (this will focus on year-on-year economic growth);
- Using nightlight data, identifying the distribution of economic activity across different geographical areas in Botswana (e.g. towns/cities, districts and sub-districts) and estimating how economic growth rates vary across geographical areas;
- Identifying the impact of the closure of the BCL mine on the level of economic activity in the town of Selebi-Phikwe and the surrounding areas; and
- To analyse the trend in economic activity within conservation areas (e.g. parks, game reserves and wildlife management areas).

The report is organised as follows. Section 2 reviews the available literature on the use of night-light (NL) data to track economic activity. Section 3 discusses the NL data and national statistics data used in the study and the general approach undertaken. This is followed in Section 4 by the analysis of the relationship between NL intensity and NMGDP in Botswana. It also extends this to consider the geographical distribution of NL data as a proxy for economic activity in different spatial areas including wildlife conservation areas, and the impact assessment of the closure of BCL mine on the economy of Botswana. Section 5 summarises the conclusions and recommendations.

2 Literature review

2.1 Nightlights and Economic Activity

Nightlights have been used to track human economic activity for the past few decades. This became possible after the US federal government declassified nightlights data in 1972 (Donaldson & Stoneygard 2012). In this section we review the literature on nightlights and economic activity, as follows. Section 2.1.1 will focus on the usefulness of nightlights in tracking human economic activity, Section 2.1.2 will review previous correlation statistics between nightlights and GDP, Section 2.1.3 will look at the relationship between nightlights and income growth and finally Section 2.1.4 reviews previous applications that have explored the relationship between income growth and nightlights.

2.1.1 Nightlights and Human Activity

Early research by Croft (1978) showed that night-time satellite images could reflect human economic activity by capturing man-made luminosity. Elvidge *et al.* (1997) took the research further by creating a "stable lights" data set based on satellite imagery. The stable lights further separated artificial lights produced by human settlements and facilities from naturally occurring lights such as solar flares and other forms of short-term lighting which are considered white noise in the data. Using the results, the authors then produced the night-time stable light (NSL) images.

Sutton *et al*. (1997) use the nightlights data along with population data from the 1992 United States census to explore how well nightlights predicted population density in the US. Analysis of the two variables returned an R^2=0.26. The authors explained that the low correlation statistic was due to nightlights images being heavily saturated in regions that are densely populated. Mellander *et al.* (2013) employ both correlation analysis and geographically weighted regressions to investigate the relationship between nightlights, differentiated into radiance and saturated light, wages, population and establishment density in Sweden. The results from the correlation analysis indicate a strong correlation between both radiance and saturated light and population density, R^2=0.763 and R^2=0.725 respectively. The paper further concludes that nightlights are a better proxy for the degree of urbanization defined as population & establishment density than for total population, production or wages. The authors highlight the severity of the saturation problem present when attempting to use nightlights as a proxy. This problem could however be solved by using more recent VIIRS NL data which we have employed in this study[1].

There have also been attempts to track both poverty and income inequality using NL data. Differences in nightlight intensity and its distribution between regions could be used as a proxy for income distribution and to identify rural, underdeveloped (unlit) regions. This would be particularly useful for inequality as data is rarely both available and reliable. Elvidge et al. (2009) use nightlights along with LandScan 2004 data to create a global poverty map. Furthermore, they constructed a normalized poverty index (NPI) which was then calibrated to form an estimation of poverty levels across the globe. The Night Light Development Index (NLDI) developed by Elvidge *et al.* (2012) using nightlights and population density data is an empirical satellite image which maps the distribution of lights across

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[1] Older studies use a system called DMSP-OLS, while work uses VIIRS data. Full details of the two different systems are provided in Section 3 of this paper.

human populations on a global scale. However, the authors of the paper highlight that the low correlation between NLDI and traditional income Gini coefficients means that the index cannot be used as a proxy for inequality at the country level. The NLDI should instead be used as a proxy for human development more generally, as it is highly correlated with the Human Development Index (HDI), electrification rates and poverty rates. The major shortcoming of both Elvidge *et al*. (2009) and Elvidge *et al.* (2012) is that they are both time-invariant measures and do not show how nightlights perform as a proxy for changes in these indicators over time.

2.1.2 Nightlights and GDP

Various papers have examined the correlation between nightlights and GDP. One of the first was Elvidge *et al.* (1997), which used the DMSP-OLS data set for 21 different countries to run regression analysis. Their research was, however, not limited to the relationship between nightlights and GDP but included population and electricity consumption. This early paper found a strong correlation between nightlights and GDP.

More in line with our approach, Sutton and Constanza (2002) look at the correlation between luminosity and state-level economic output in the United States for the year 1995. Their research returns a strong log-log correlation coefficient of R^2=0.86. Doll *et al*. (2006) extend this work by testing the degree of correlation between nightlights and GDP at the subnational level across the United States and 11 members of the European Union. Luminosity was found yet again to correlate with regional output across a range of spatial scales. Bhandari and Roychowdhury (2011) further extend the subnational output and nightlights analysis by focusing on an emerging economy, India. They find very low linear correlation between GDP and the sum of nightlights. However, the log-log correlation coefficient returned between the two variables was very high, R^2=0.87. The means that the GDP and sum of nightlights series were only strongly correlated at the subnational level once they had undergone log transformation which helps reduce the skewedness of the series.

With most of the literature supporting the argument for a strong and positive correlation between GDP and nightlights, Ma *et al.* (2012) attempt to determine the best fitting model for the relationship between the two variables. The authors test the best fitting model using city level data taken from a total of 252 cities in China over a long term, 16-year period (1994-2009). The three regression models that were tested were the power linear model (considers whether GDP is proportional to nightlights raised to a power), linear model and exponential model. Of the sample, the power linear regression model was the best fit for 167 cities, followed by the linear regression model with 82 cities and finally the exponential regression model with 3 cities.

Using nightlight data to estimate GDP at the subnational level has been carried out by Ghosh *et al.* (2007). Their paper uses two methods in their estimation. The first method simply relates the sum of nightlights to a GDP figure and the second attempts to resolve the saturation problem associated with DSMP-OLS data by applying "a spatial analytic approach to the patterns in the night-time imagery as they relate to population density." The study utilizes DSMP-OLS data and national accounts data from four countries, namely China, India, Turkey and the US for the year 2000. Following the first model, the estimated GDP for India, Turkey, China and the US resulted in estimation errors of 35%, 187%, -16% and 0% respectively from the actual recorded GDP figures. Positive percentage errors were recorded when the nightlights estimate for GDP was greater than the recorded national accounts figure and negative percentage errors reflected the opposite. The estimated GDP when using the second model presented significantly less errors with China, India and the US registering 0% errors and Turkey recording an error of 103%. The shortcoming of this study is the fact that the models adopted to predict/estimate GDP are very crude and do not attempt to correct for the structural differences between countries, such as the composition of GDP by sector, which affect the relationship between nightlights and GDP. The authors do however conclude that the crude measures they had used to develop these GDP estimates may be useful when attempting to map economic activity at the subnational level given the low estimation errors.

2.1.3 Nightlights and Income Growth

This section explores the link between income growth and nightlights. The literature on this nexus is not extensive, as it is a relatively new field.

Henderson *et al.* (2012) is the first paper to utilize nightlights to measure real income growth by using an econometric framework. They employ three different statistical specifications on a panel data set of approximately 188 countries between the years 1992-2008. The first specification was used to find the elasticity between income and night lights (referred to as "Henderson elasticity"). This was done by regressing GDP against the sum of nightlights in log linear form. The specification controlled for both country fixed effects and time fixed effects in order to avoid potential bias caused by external factors such as technological advancements and cross border cultural differences. The second specification was used to predict growth fluctuations from a country's long-run growth path. This was achieved by adding a country-specific time trend to the first specification. The third and final specification regressed *changes* in GDP against *changes* in nightlights (i.e. in differenced form). The time period for this regression was reduced to 1992-2006 due to data limitations. The third specification was adopted in order to focus on long-term growth. The results from the first specification estimate the elasticity between GDP and nightlights to be 0.277, statistically significant at the 1% level. This means that a 1 percent increase in nightlights is associated with a 0.277 percent rise in GDP. When other control variables are added the elasticity figure then lies within the range of 0.261-0.286 and remains statistically significant at the 1% level. The results also suggest a quadratic relationship between GDP and nightlights does not exist; this is unsurprising given the strong linear and or log-linear correlation that has been established between nightlights and GDP. When the time specific trend is added, the value of the elasticity falls to 0.180 but remains statistically significant at the 1% level. The authors conclude that the high significance of the elasticity figure means that nightlights track fluctuations well. The long difference specification returned a slightly higher elasticity figure of 0.320, which was still statistically significant at the 1% level. The downside of this analysis is that it does not deal with the endogeneity issues that are present between income and nightlights. The reverse causal relationship between the two variables means that the elasticity value that is estimated suffers from bias.

There have been a few studies that have attempted to replicate the results of Henderson *et al.* (2012). Beyer *et al.* (2018) apply the same methodology to a global sample of countries and then separate out a group of 8 South Asian countries to isolate the elasticity for them specifically. The elasticity for all countries was 0.267 and for the South Asian region alone was 0.248. Both estimates were significant at the 1% level. The lower elasticity of the South Asian countries was attributed to their larger than average agricultural sector. Nightlights are not as strongly correlated to economic activity in the agricultural sector as compared to manufacturing and services, due to the fact that some of the activity does not produce light. This is further evidenced in the paper as they compute Henderson elasticities by sector from the global sample of countries. As expected, agriculture had the lowest figure with 0.13, followed by manufacturing with 0.37 and services with 0.43.

Bundervoet *et al.* (2015) also replicate the study of Henderson et al. (2012). They apply it to a data set of 46 Sub-Saharan countries over a 21-year period (1992-2012). They derive a Henderson elasticity of 0.567 which is statistically significant at the 1% level. This is much higher than that derived by Henderson *et al.* (2012). The authors argue that this is due to the largely under-developed nature of the region. Increases in GDP in unlit areas (which may become lit) are more likely to have a larger impact on lighting than in places that are already lit. The results from this study differ from Henderson *et al.* (2012) in that they find a negative and weakly statistically significant (at the 10% level) quadratic relationship between nightlights and GDP. The authors however explain that the quadratic relationship is not robust to different sample specifications and was driven by the inclusion of Equatorial Guinea, where nightlights grew much faster than GDP, in the sample.

2.1.4 Application of Nightlight Data

The papers mentioned in the previous section derived Henderson elasticities for various applications. Those that are similar to our application of the data will be explored.

Beyer *et al.* (2018) use nightlights and derived Henderson elasticities to investigate the affect that major shocks have had on economic activity in various countries within the South Asia region. Firstly, they investigate the effect of the two earthquakes suffered by Nepal in April and May 2015, as well the trade disruptions with India in August of the same year. The authors find that the trade disruptions had a larger impact on income growth than the earthquakes. The areas affected by the earthquake experienced a decline in their regional GDP of 1.8 % in April/May 2015 when compared with the same period in the previous year. Regions which were not affected by the earthquake grew slightly over the same period. With regards to the trade disruptions with India, the authors compared the GDP growth rates in September/October 2015 with those in the previous year. The study shows that districts within the Terai region which is close to the Indian border had a GDP contraction of 9.0 % whereas other districts declined by only 1.4 %. Secondly, the authors investigate the conflict outbreaks in Afghanistan. They find that each additional death/injury per 1000 people has a negative and statistically significant impact on local GDP growth during the same month and quarter. The authors did however not find a statistically significant relationship between annual GDP growth and conflict.

Bundervoet *et al.* (2015) use the Henderson elasticity derived from the long-differenced regression to estimate the subnational GDP growth in Kenya and Rwanda using growth in nightlights. For Kenya, nightlights estimated growth to be 4.0 percentage points between the years 2000-2012, slightly lower than the 4.2 percentage point growth recorded by national accounts for the same period. Furthermore, the authors were able to compare the long-term growth rates for the various districts within the country. In the case of Rwanda, nightlights over-estimate the GDP growth during the early 2000's. the authors attribute this to the rapid recovery of lights compared to GDP following the genocide in the country. This period of over-estimation was then followed by stagnation in nightlights growth between 2000-2005. Overall, the GDP growth estimated by nightlights between 2000-2012 was 5.4 percentage points, significantly lower than 8.0 percentage point growth recorded by national accounts. The large under-estimation of income growth could be attributed to the fact that nightlights would not be able to pick up agricultural output as it is mainly unlit, which is important given Rwanda's high dependence on agriculture, which in 2012 accounted for 33 percent of total GDP. At the subnational level, average GDP growth rates could only be estimated for 16 of the 30 districts due to the others having insufficient lighting. GDP growth estimates for the 16 districts in Rwanda show that Kamonyi, Nyanza, and Musanze Districts were the fastest growing districts between 2000 and 2012 at an average annual growth rate of 9.9 %, 8.3 % and 7.1% respectively between 2000 and 2012. Rubavu, Karongi, Gicumbu, Nyamagave and Rwamagana grew at more than 5% and were the second fasted growing group. Gasabo district, Kicukiro and Nyarungenge districts forming the Kigali city experienced GDP growths between 4.8% and 3.3% with the slowest growing districts being Huye at 3.1 percent and Nyarugenge at 3.3%.

2.2 Application to Environmental Issues

Previous research has worked on exploring and establishing the relationship between economic indicators (i.e. GDP, income, consumption etc) and night lights (see e.g. Henderson *et al*., 2012; and Donaldson & Storeygard, 2016). This work has paved a way for application of night light data in different situations and economic sectors. The use of night lights is ideal for situations where the economic data is either unavailable or regarded poor as per the International Monetary Fund (IMF) data rankings. In those situations, the night lights provide an opportunity to measure the levels of economic activity from outer space. Also, studies have shown that the combination of the night lights and measured GDP can be used to produce better estimates for economic growth. The data has been used to measure economic activity at the local level (see Beyer *et. al.,* 2018) where such data is usually not available due to resource constraints. Other applications include the use for period of wars or genocide (Henderson *et. al*., 2012), places where GDP figures are not provided such as North Korea, inaccessible areas such as the coastal areas, or to measure the economic impact of the natural disasters such as earthquakes (Beyer *et al*., 2018).

Interestingly, some of the literature is starting to apply NL data to environmental issues. Most work on the application of nightlights data to environmental issues, include estimation of non-marketed values (e.g. some environmental services) and estimation of the ex-ante and ex post impact of natural disasters on economic activity at a much-disaggregated level.

For example, on estimating the value for environmental services using night lights, Valle et al. (2019) estimated the economic value of mangroves in Central America (see Valle et al. 2019). The study estimated the capacity of the mangroves to protect vulnerable assets and economic activity from hurricanes. The authors estimated the causal impact of hurricanes on economic activity by regressing the economic nightlights on the damage index from hurricanes at a more disaggregated geographical area of 1 km^2. The study found out that night lights decrease by up to 24% in areas that are *unprotected* by mangroves hence stressing the economic value of the mangroves in Central America. Valle *et al.* (2019) further concluded that hurricane damage also declines with mangrove width and that the effect of hurricane is entirely mitigated by one km or more of mangrove width. Additionally, in determining the value for ecosystem services, Li and Fang (2014) used night lights to predict global marketed and non-marketed (ecosystem services) economic activity using nightlight and landcover satellite images at a high-level spatial resolution (1 km^2). The ecosystem services market was estimated using land cover data set and estimated unit ecosystem values per hectare. The nightlights and landcover data showed that while GDP is concentrated in northern industrialised countries, ecosystem non-marketed value is concentrated in tropical regions, wetlands and other coastal systems. The study indicated that the marketed values and non-marketed values could then be used to measure the ecological deficit of countries at a high-level spatial resolution (1 km^2).

Other studies have applied night lights to measure the impact of natural disasters on the economy at a more disaggregated level. Ishizawa *et al.* (2017) has used night lights data and storm tracks satellite data from NOAA to estimate the impact of hurricane strikes on economic activity in Central America. The study used Henderson *et al.* (2012) analytical methods and wind exposure-based damage function by Emmanuel (2011) to conclude that major negative economic impacts of hurricanes in Central America were concentrated on the first year of the strike with an impact ranging from -2.4% to -3.5% of GDP growth. Moreover, Bertinelli *et al*. (2016) has also used hurricane tracks and nightlights as a proxy for economic activity to conduct an ex-ante assessment of the economic impact of hurricane storms in the Caribbean region. The study estimated the expected risk or losses if a hurricane occurs in the future in the Caribbean region. The expected damages were distinguished according to use, size, type of roof and construction, wall types and region. It was predicted that the damage for certain areas like Anguilla, Cayman Islands, Jamaica, Saint-Martin and Sint Marten will be at an average of 2% of GDP in less than five years with the total damages at $US 187 million for the entire Caribbean region and an average of $US 20 million for a number of countries.

In addition, night lights have been used to also measure the impact of typhoons on economic activity at a disaggregated level. Strobl (2019), followed the approach of Bertinelli *et al.* (2016) and Ishizawa *et al.* (2017) to estimate the economic impact of typhoons in the Philippines. The study used NL data from 1992 to 2013 and storm data dating back to 1950 to predict the expected return of typhoons and the likely damage in the Philippines. The study found out that typhoons with return periods of at least 5 years are likely to cause a 1% short-term reduction in economic activity whilst those with return periods of at least 20 years are likely to cause a reduction of around 2% in economic activity.

3 Approach and Methods

3.1 Night-Light Data

This study uses data derived from the Sumi Solar Polar Partnership (SSPP) satellite jointly flown by National Oceanic and Atmospheric Administration (NOAA) (NOAA) and NASA (Elvidge *et al*. 2013). The Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) used in this study is an improvement on the earlier data collected by the US Air Force Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) satellites between 1992 and 2013. The release of DMSP-OLS data was discontinued in 2013, while the new VIIRS Day/Night Band (DNB) data commenced in 2012 and is available to 2018. The VIIRS data has notable improvements over the DMPS-OLS data, including a reduction in the pixel footprint (ground instantaneous field of view [GIFOV]), uniform quantization, and in-flight calibration. This improves the pixel values[2] and improves the computation and correlations between GDP/national statistics (see Elvidge *et al*., 2017).

Collection of the DMSP-OLS data was an originally meteorological initiative of the US Defence Force department to detect clouds using moonlight. However, the satellite had the capability of detecting lights from cities, gas flares, shipping fleets and fires as by-products of the project.

The DMPS-OLS and the VIIRS data are available for public use[3]. Using these data as a proxy for economic activity requires the exclusion of non-economic lights to create “stable lights” that are free from extraneous lights such as moonlight, fires, gas flares etc. This process is described later in the section.

The switch by NOAA/NASA from the DMSP-OLS data to VIIRS data creates some constraints to the use of NL data for economic analysis. The two NL datasets cannot be combined, hence creating a structural break, with one longer but older data series (DMSP-OLS) from 1992-2013, and a shorter but more recent one (VIIRS), from 2012-18.

This study uses the VIIRS data, as the intention is to focus on recent changes in economic activity in Botswana, notwithstanding the shorter data series. The VIIRS data are also of better quality in terms of predicting economic activity. The VIIRS/DNB NL data is available as monthly and annual composites from the NOAA website. The annual data is a set of stable light corrected for extraneous lights unrelated to economic activit but is currently only available for 2015 and 2016 from NOAA. Monthly data is available for the entire period, but is uncleaned, and requires to be cleaned to create annual stable night lights for years that have not been cleaned. The process of cleaning the data to create annual stable lights is technical and time consuming (see Elvidge *et al*. 2017). Studies have developed different methods that can be used to clean the data. For example, Beyer *et. al* (2018) proposes three strategies that can be used to clean the monthly data. The *first strategy* involves sampling night lights from places that lack human activity such as national parks, forests and mountain ranges while the *second strategy* entails removing all observations from areas seen as “background noise mask”. The second step involves identifying outliers and then clustering observations based on their intensity. *The third strategy* means removing outliers and observations from locations with background noise. To execute the steps for the last approach, a stable annual composite data is used as a mask to remove

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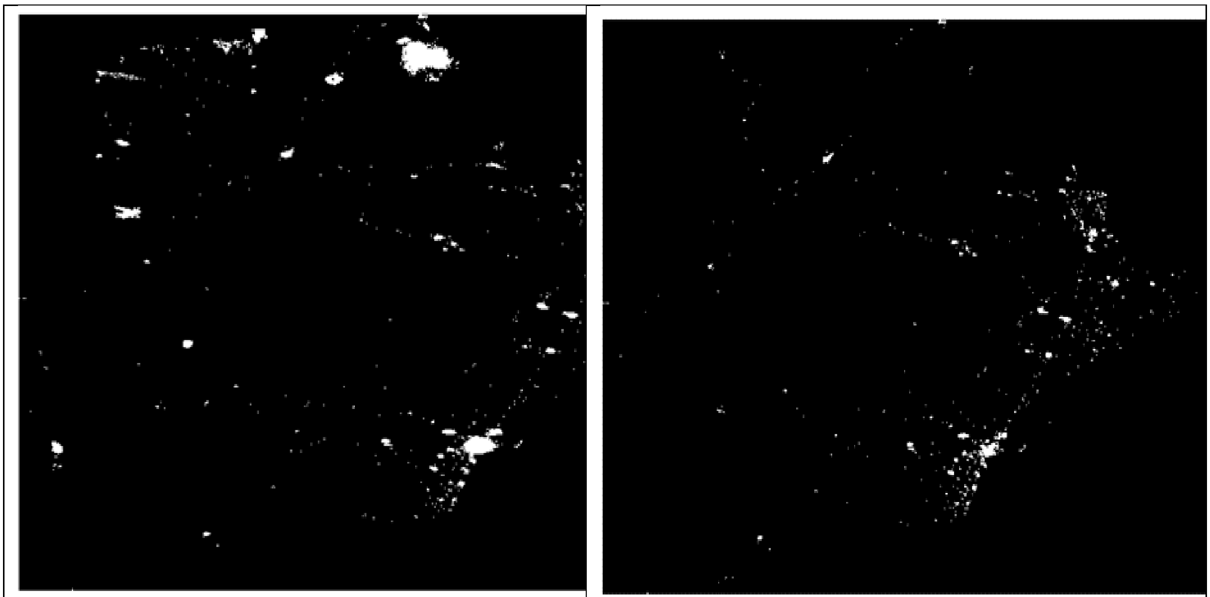
[2] For example, ground footprint for DMSP-OLS is at 5km x 5km nadir compared to 742 x 742 m by VIIRS making the footprint of the VIIRS to be 45 times smaller than the DMSP-OLS.

[3] https://www.ngdc.noaa.gov/eog/viirs.html

background noise from monthly data using GIS software. The first and second approaches are suitable for small areas and a short time trend as they are labour intensive. For example, the method identifies and selects pixels with the largest or important information and disregard those that are mostly noisy. The third approach requires less time than the other approaches but does not allow the investigation of changes in newly lit areas, only to observe changes in brightness within the same locations.

Our study adopts the last strategy to clean the VIIRS monthly data from 2013 to 2018 using the available 2015 and 2016 annual stable data as masks. The 2015 annual nightlight composite mask was used to clean months in years closer to 2015[4] and the 2016 annual nightlight composite mask for months years closer to 2016[5]. The final steps in processing the data include aggregation of the monthly data according to years and quarters to create the needed data for analysis. Analysis of data was done using GIS software to compute zonal statistics using vector shape files such for national Botswana border, districts borders, protected area borders and enumeration areas (commonly villages)[6] as geographical levels at which the nightlights are aggregated. The following images in figure 1 show the differences in the images after and before removing unwanted lights.

Figure 1: Images showing night-lights before and after cleaning



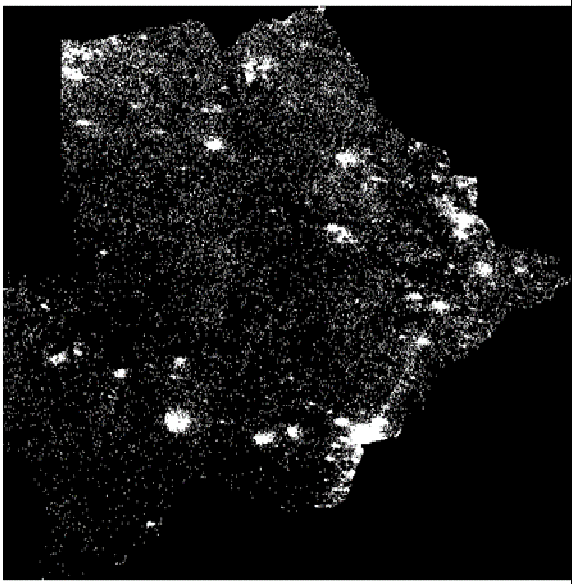
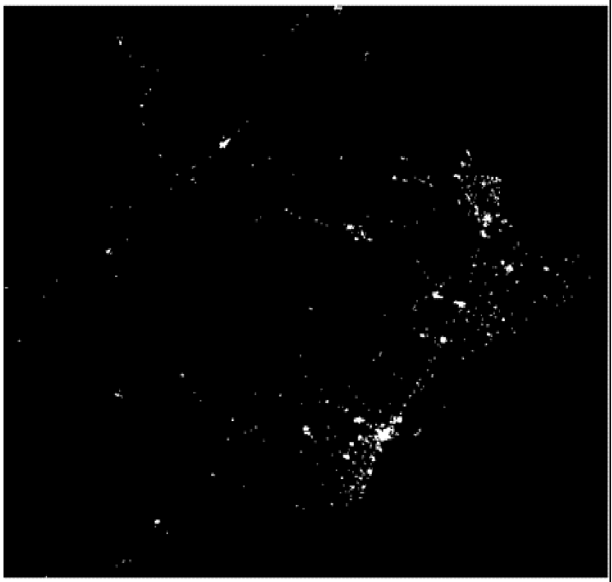
(a) Uncleaned data for October 2018

(b) Cleaned data for October 2018

[4] 2013, 2014, 2015.

[5] 2017,2018 (this was done to reduce the effect of not observing changes in newly lit areas).

[6] The analysis used shape files purchased from Statistics Botswana with geographical areas based on the Enumeration Areas used in the 2011 census.

	
(c)[7]Uncleaned data for November 2018	(d) Cleaned data for November 2018

3.2 National Accounts Data

The national accounts data for Botswana is compiled by Statistics Botswana (SB) and published quarterly. The data lags real time by approximately one quarter and data from the most recent two years are cited as provisional estimates, meaning they are subject to review and could possibly be adjusted.

The National Accounts break down national GDP by both economic activity and expenditure, at both current and constant prices. The economic expenditures categories reported include Government Final Consumption, Household Final Consumption, Gross Fixed Capital Formation, Change in Inventories, and Exports and Imports. Economic activities are separated into ten categories (excluding taxes), the largest of which are Trade, Hotels & Restaurants; Mining; General Government; Financial & Business Services. The national accounts are compiled according to the System of National Accounts (SNA) 1993, which is an internationally standardized set of recommendations used to measure national economic output. The data is sourced mainly from surveys and administrative records and is only available at the national level. National accounts are published in both current prices and constant (2006) prices. The constant price series excludes the impact of price changes, and values economic activity and expenditure at base year (2006) prices, hence providing a measure of real economic activity.

Although following best practices, there are a few concerns over the accuracy of the data. The first is that the base year is now out of date and provides an inadequate reference point for real GDP[8]. A second relates to uncertainties over the largest single component of GDP by expenditure, Household Final Consumption, which is not measured directly, and which according to the published data has grown at an implausibly fast rate[9]. This suggests that household consumption data might be over-

7 *(c)* showing a high presence of moonlight.
8 An exercise is currently under way to re-base the national accounts to 2016
9 According to the national accounts, household consumption in Botswana had an average cumulative annual growth rate (CAGR) of 12.2% between the years 2009/10 and 2015/16, which is much greater than the 5.6% average CAGR in

estimated, which may imply that overall GDP levels (and historical growth rates) are also over-estimated.

This study utilizes the Botswana national accounts data over a five-year period between 2013 and 2018. Specifically, the real annual GDP figures are used to establish the correlation between income growth over this period and the growth of nightlights.

One issue to consider is whether the national accounts data, and the relationship between nightlights growth and GDP growth, needs to be adjusted to account for the agricultural sector in Botswana. If the agricultural sector within an economy is large, then nightlights will underestimate the true level of economic activity. This is because agricultural activity is mainly unlit, especially at the subsistence level, and will not be captured by nightlight images. This would be especially problematic when comparing growth rates between urban, lit areas, and rural regions which typically rely on agriculture. In Botswana, however, the agricultural sector is relatively small (2% of GDP), and this is unlikely to be a significant problem.

3.3 Methodology

The methodology used in this paper is straightforward and based on descriptive methods. At present there is insufficient data to utilise more detailed analytical techniques, with a relatively short time series for the night lights data and a lack of geographically disaggregated economic data. The analysis is therefore based on comparison of levels and growth rates of available economic data and the night lights data.

formal earnings from employment during the same period. Household final consumption is not measured directly on an annual basis, but only intermittently in household income and expenditure surveys. Over the same period, survey-based measures of household consumption show 6.5% a year average annual growth.

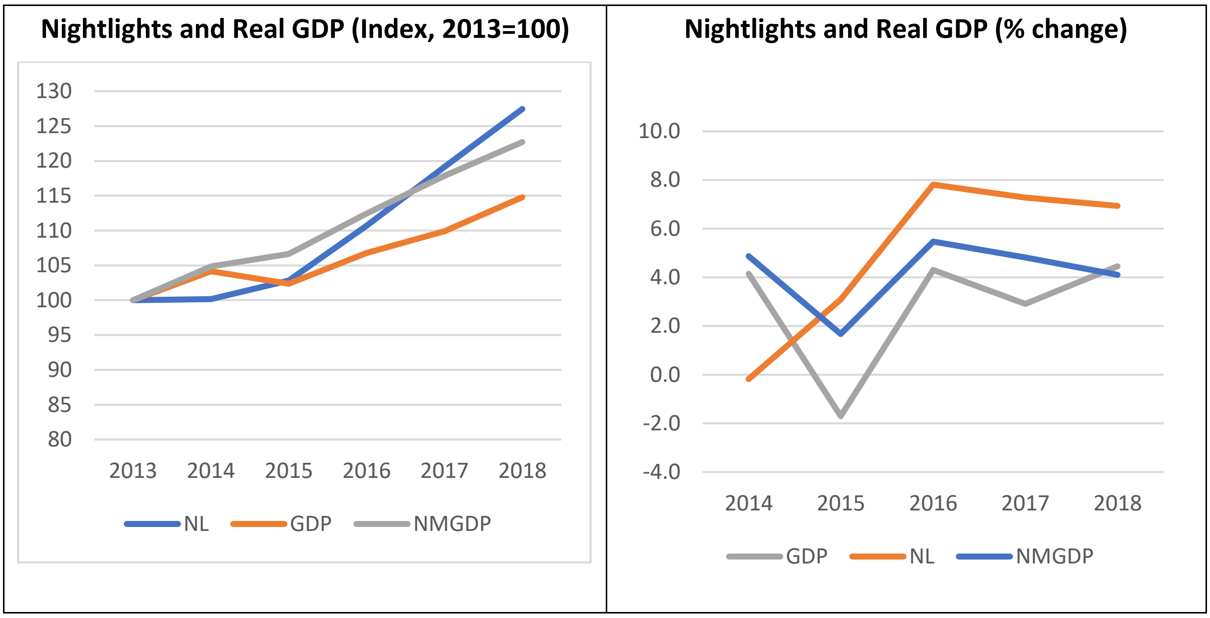
4 Results and Discussions

In this section we present the results for the relationship between Botswana's national GDP and night lights. We also present results for value added and GDP growth in Botswana from the share and growth of NL data.

4.1 Link between Night Lights and GDP at the National Level

Statistical correlations between nightlights and two different measures of GDP – total GDP and NMGDP were computed to see how NL and GDP are related in Botswana. This was done for both absolute levels and growth rates.

Figure 2: Nightlights and GDP



Source: Statistics Botswana and own calculations

Table 1: Correlations between Nightlights and real GDP growth rates

	GDP	NMGDP
2014-2018	0.326	0.369
2015-2018	0.945	0.972

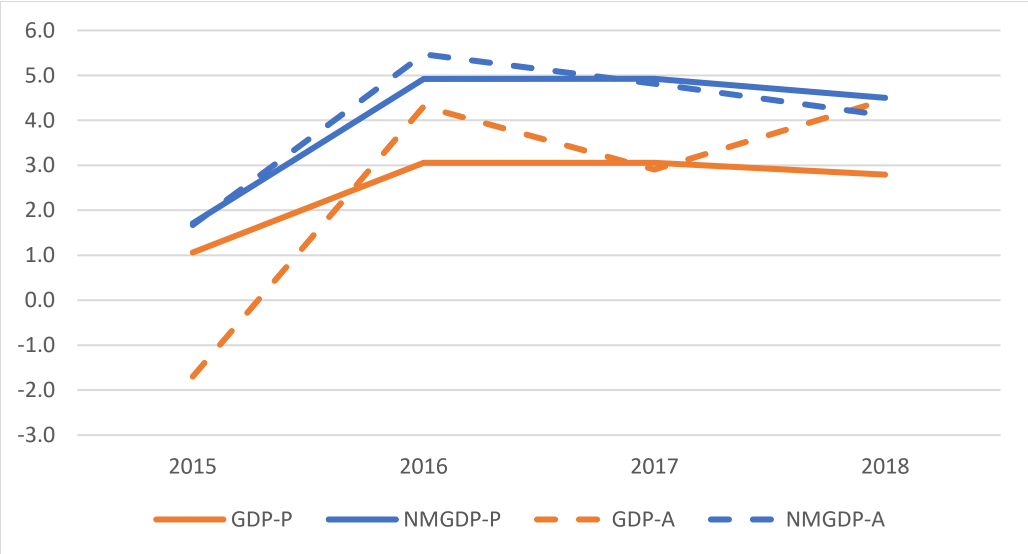
These results suggest, firstly, that the year 2014 was an outlier in terms of growth rates, with virtually no NL growth. Hence the correlation between NL on the one hand and (NM)GDP is much higher over 2015-18 than over 2014-18 (Table 1). Second, the correlation with NL is slightly higher when NMGDP is used than when total GDP is used. We therefore use NMGDP as our measure of economic activity going forward. A correlation of 0.97 was established between NL and economic activity (NMGDP) from 2015 to 2018.

Elasticities between NL growth and economic growth were also calculated[10]. The figures were 0.40 for NL and total GDP growth, and 0.64 for NL and NMGDP growth[11]. This means that a 1% growth in NL is associated with a 0.64% growth in NMGDP. This elasticity is comparable to the one computed by Bundervoet *et., al*. (2015), which found an elasticity of 0.56 for short term (annual fluctuations) growth and 0.55 for long term growth (2012-2000) in Sub-Saharan African countries (based on a panel of 46 countries over 21 years). Beyer *et. al*. (2018), found a lower elasticity of 0.4 in India. The results give enough confidence to use our estimated elasticity to link NL growth with NMGDP growth.

The high correlation (97%) between NL and economic growth in Botswana is expected, as this study used better data (VIIRS) than the old data (DSMP-OLS). Most previous studies have used the DSMP-OLS data to estimate economic activity. The VIIRS has a smaller pixel footprint and hence a better measure for light-intensity from outer space. The DSMP-OLS also creates background noise which is difficult to clean hence affecting correlation compared to the VIIRS data.

Figure 3 shows actual (measured) and predicted (using night lights data and the estimated elasticity) economic growth for both total GDP and NMGDP. As the figure shows, the relationship between predicted (P) and actual (A) growth is much higher for NMGDP than for total GDP[12].

Figure 3: Actual (A) and Predicted (P) Real Economic Growth (%) for 2015-2018



Source: Statistics Botswana (GDP) and own study estimates.

10 These were not estimated though regression analysis, as in the literature discussed above, due to lack of time series data. The elasticities were calculated simply as the average economic growth rate divided by the average NL growth rate over the period 2015-2018.

11 Sectors in the economy may have different have GDP-night lights relationship. For example, elasticity for short term fluctuations in production may be different to long term fluctuations. GDP levels tracked by lights in tourism may be different to other sectors.

12 This discrepancy may reflect the nature of the mining sector in Botswana, which is dominated by diamond mining. Growth in mining value added is largely determined by changes in the level of diamond output, and this may not involve much in the way of changes in the amount of luminescence at the mines, which operate on a continuous basis regardless of the level of actual output.

4.2 Regional and Urban/Rural Economic Growth

Botswana relies on national statistics to measure levels of economic activity. The national statistics do not provide any information on economic activity at the district/local level. This results in an important gap, for instance on the distribution of economic activity between urban and rural areas, or on relative economic growth rates in different parts of the country. This is important from the perspective of determining whether the benefits of economic activity and growth are being shared across the country. This is especially so because other socio-economic data, derived from household surveys, show that poverty rates and income levels vary considerably between urban areas, urban villages, and rural areas.

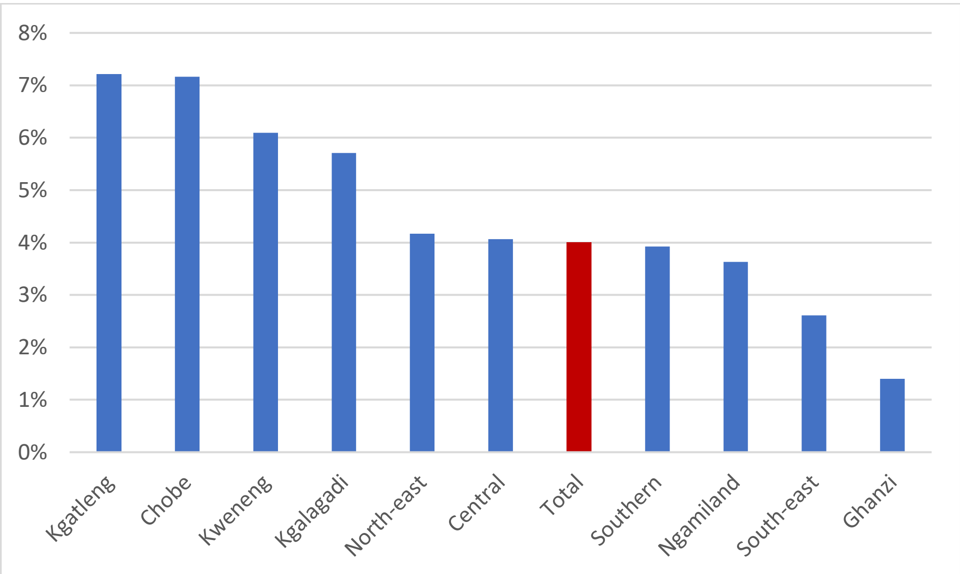
Other NL studies have found innovative means to estimate the sub-national distribution of GDP and changes over time (e.g. Bundervoet *et., al*., 2015 and Beyer *et. al*., 2018). Following this approach, we have used the Botswana NL data to estimate the subnational distribution and growth of NMGDP (value added) in Botswana.

4.2.1 District level NMGDP Growth

The NL data were used to estimate economic growth at the regional level using the elasticity estimated from the association between NL growth for Botswana and the national NMGDP growth. The results presented in Figure 4 shows average annual NMGDP growth per district as predicted by the nightlights from 2015 to 2018. While district-level growth is positive across all districts, there is considerable variation. There are four fast-growing districts (Kgatleng, Chobe, Kweneng and Kgalagadi), two slower growing ones (Ghanzi and South-east), with the remainder close to the national average (North-east, Central, Southern and Ngamiland).

There is no obvious pattern to the fast and slow growing districts, whether geographically or more / less urbanised. For instance, both Kgalagadi and Ghanzi districts are large, sparsely populated districts in western Botswana, without large urban areas, but one is relatively fast-growing, the other slow. Similarly, two districts that, in part, are close to Gaborone – Kgatleng and Kweneng – are fast-growing, while the similar South-east district was one of the slowest growing.

Figure 4: Non-Mining GDP growth for Districts (annual; average annual 2015-2018)



4.2.2 NMGDP growth across different types of settlements

Districts include settlements of different sizes, and therefore a mixture of types of economic activity. It is useful to consider different types of settlement:

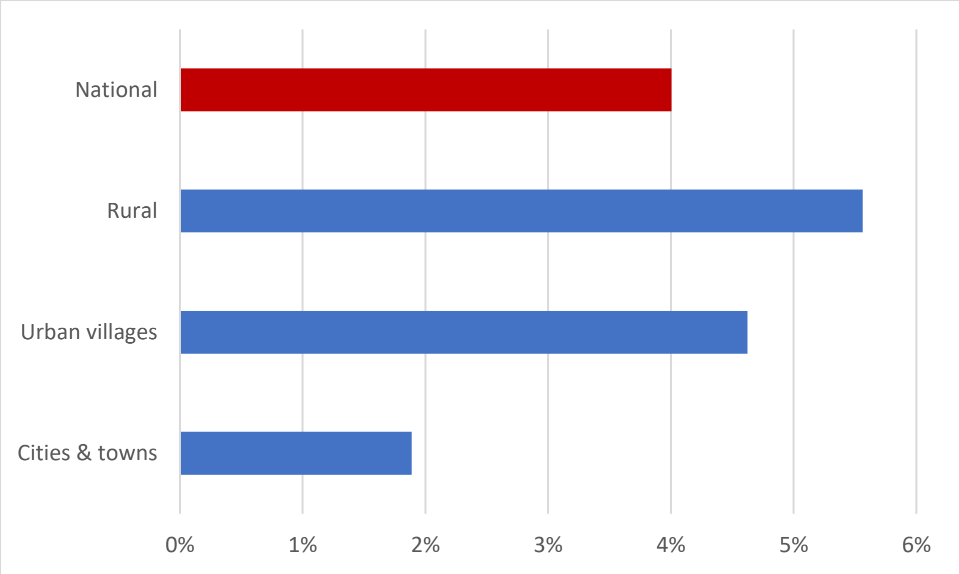
1. **Cities and towns**: urban settlements with separate administrative structures (City and Town Councils);
2. **(Large) Urban Villages**: According to the Statistics Botswana definition and categorization, an urban village is a settlement with a population of 5,000 people or more, that is not primarily dependent upon agriculture, but without its own administrative structure; i.e. it is administered by the relevant District Council. For present purposes, the focus is on "large" urban villages, with a population of 20,000 or more, along with some smaller ones on the periphery of Gaborone.
3. **Rural and small urban villages**: settlements outside cities, towns and large urban villages[13].

The distinction between cities/towns and large urban villages is primarily in terms of administration, rather than size. The largest urban villages (Molepolole, Maun, Mogoditshane and Serowe) have populations of over 50,000, making them larger than all of the towns, and are only smaller than the cities of Gaborone and Francistown. Similarly, the smallest towns (Sowa and Orapa) have populations of less than 10,000 and are smaller than many urban villages.

An examination of NMGDP growth rates derived from the NL data shows significant contrasts between these three area types. As Figure 5 shows, the fastest growth has been in rural / small village areas, followed by urban villages and cities / towns. This is likely to reflect various factors, including the progressive roll-out of rural electrification to smaller settlements; the impact of redistributive policies such as infrastructural developments and poverty alleviation policies benefitting poorer locations, and the fact that cities and towns are constrained by administrative boundaries, whereas urban villages are more able to grow physically as development takes place. But it is nonetheless an interesting conclusion, which contrasts with our expectation that growth is concentrated in urban areas.

[13] We have used the term "rural" to describe this segment, but this could be misleading. First it includes some quite large settlements (urban villages with populations from 5,000 to 20,000). It also includes Mahalapye, an urban village with a population of almost 50,000, but for which the geographical shape files were incorrect. Finally, and this may be the most important exception, it includes mining areas where the mines are located outside of towns, notably the Jwaneng, Orapa and Karowe diamond mines.

Figure 5: Implied Non-Mining GDP growth rates, average 2015-18, by type of settlement



These results across the different localities may be compared to the poverty estimates of 2015/16 by Statistics Botswana (2018). The results show that during the period from 2009/10 to 2015/16, poverty increased from 8.0 to 9.4% for cities/towns while in urban villages decreased from 19.9% to 13.4%. In rural areas it decreased marginally from 24.3 to 24.2%[14].

The same trends can be examined in more detail by considering more disaggregated growth rates at the level of individual settlements (Figure 6). Key results are as follows:

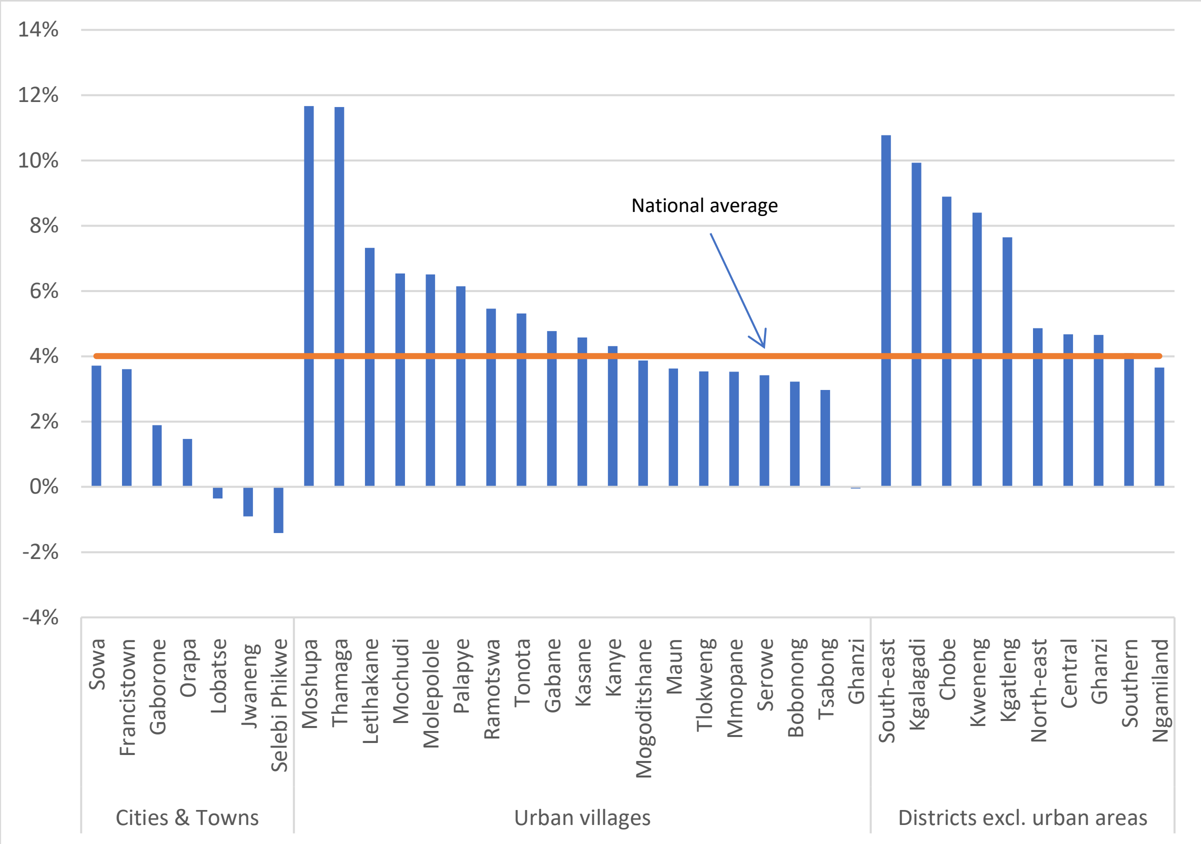
a. **Cities and towns**: apart from Sowa (which is very small), the fastest growing urban area was Francistown, which is surprising given perceptions of a slowing of economic growth but may reflect a high level of infrastructure development in the city. Selebi-Phikwe experienced negative growth over the period, reflecting the closure of the BCL copper-nickel mine.
b. **Urban villages**: the fastest growing settlements were mostly those close to Gaborone – essentially those that are within commuting distance of Gaborone but are not part of the Gaborone peri-urban area. These villages include Moshupa, Thamaga, Mochudi, Molepolole and Ramotswa. Others amongst the fastest growing urban villages are driven by location-specific factors, including Letlhakane (the centre of a diamond mining area) and Palapye (along the highway A1 with major public investments in the form of a new university and power station). It is encouraging that there are several settlements enjoying robust growth that are not being driven by economic activity in Gaborone[15].
c. **Rural districts**: three of the five fastest growing rural districts are those surrounding Gaborone (South-east, Kweneng and Kgatleng), suggesting that the same trends of growth in the Gaborone travel-to-work area are at play, affecting smaller settlements as well as larger ones. The two other fast-growing rural districts – Chobe and Kgalagadi – are at opposite ends of the

[14] Note that the definition of urban village used in the poverty data includes all urban villages, whereas the definition used for NL purposes includes only the larger urban villages.

[15] Besides Letlhakane and Palapye, these include Tonota, Kasane and Kanye.

country and their fast growth may reflect local factors as well as the fact that the growth is of a very low base.

Figure 6: Implied Non-Mining GDP growth rates, average 2015-18, by major settlements



While NL have shown to be a reasonably good proxy for NMGDP growth at the national level (see subsection 4.1), NMGDP growth as predicted by the night lights at the regional levels should be treated with caution. For example, growth elasticities are not necessarily the same across regions as the composition of their economic activity is not homogenous, and night lights relate differently to different sectors of the economy. Bundervoet *et. al.,* 2015, argue that, if growth in agricultural GDP accounts for a sizeable total growth in the region, then NL will tend to underestimate GDP. However, the same study argues that the underestimation due to agriculture is small[16]. Prakash also argues that, population density tends to have an influence on the nightlights-GDP relationship, underestimating

[16] Bundervoet *et. al.*, (2015) carried out an analysis with around 46 countries and 966 observations (25 countries with above average share of agricultural GDP and 21 with a below average share of agricultural GDP. Both the two proportions indicated a strong association between their GDP and nightlights, indicating that even for agrarian or unlit economic activities, the association can be relatively higher. The results showed that, for every unit growth in night lights, the agrarian regions GDP grows by around 0.445 and those of less agrarian by around 0.656. Even though the same correlation coefficient of around 0.65 was found for Botswana in this study, largely because Botswana is a less agricultural area, we should probably expect different associations across districts depending on the heterogeneity of their economic activities. It is not known to what extent the coefficients should be different, but the expectation is that elasticities should be higher in districts near Gaborone. Perhaps the growth estimated (using our elasticity) can be more applicable to towns/cities Greater Gaborone and districts and villages around Gaborone and/or cities. The other cities a lesser elasticity (i.e. 0.445 can be used) when tracking different activities using night lights.

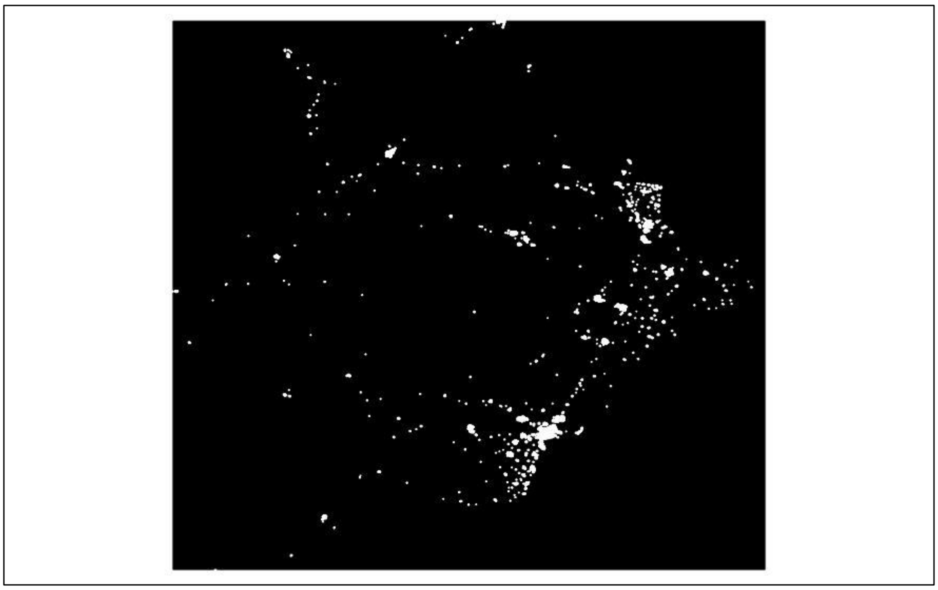
growth for densely populated regions. This problem can be corrected by a panel data estimation using different GDP levels with different population densities. However, it was beyond the scope of this study to conduct that estimation and due to lack of sufficient data.

4.2.3 Geographical distribution of NMGDP (Districts, towns/cities)

This section uses nightlights to estimate the geographic distribution of economic activity in Botswana. Since NMGDP figures are not reported at the village/town/city level in Botswana, using nightlight images as a proxy for the distribution of economic activity is potentially useful.

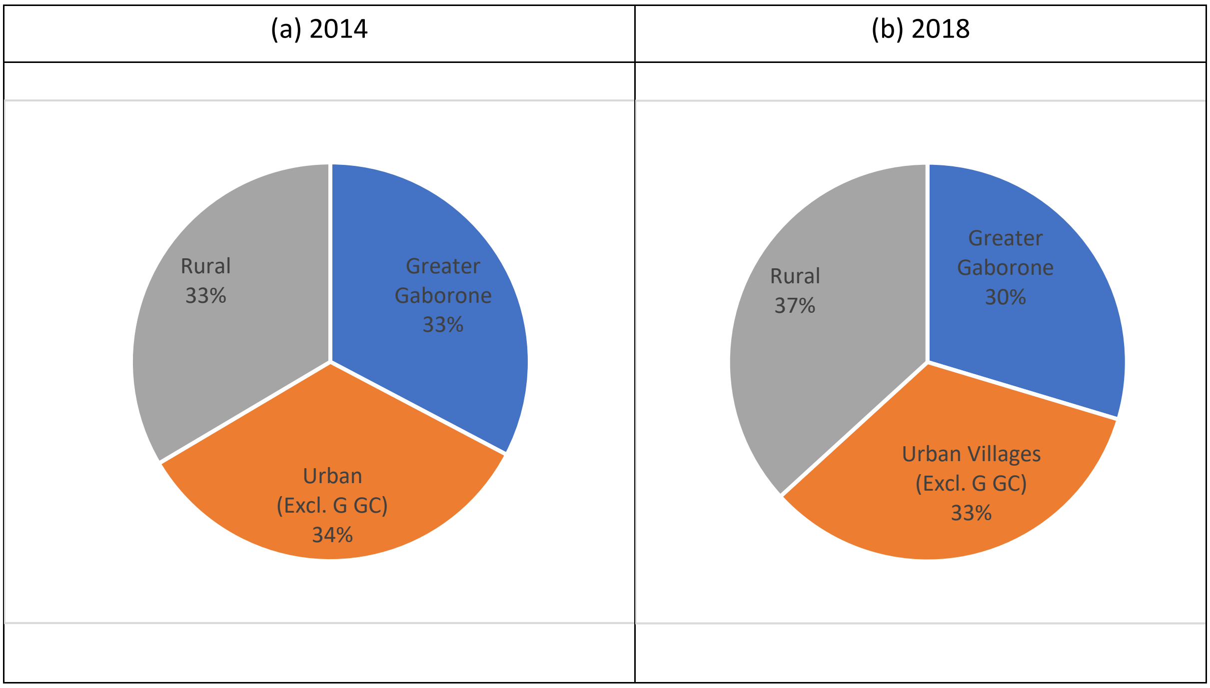
To gain a better picture of the geographic split of economic activity in Botswana, we categorise all settlements into three groups: Rural villages & settlements, Urban areas, and Greater Gaborone. Towns and villages within proximity to Gaborone are classed as part of Greater Gaborone[17]. Those that are not within this category are classed as either urban or rural, depending mainly on the size of their population. The urban category includes all cities and towns; urban villages with a population greater than 20,000; and district centres are considered urban. All other settlements and areas are considered rural.

Figure 7: GIS photo showing nightlights intensity for 2018 across Botswana



[17] Besides the city of Gaborone, this includes Mogoditshane, Tlokweng, Gabane and Mmopane

Figure 8: Shares of National Nightlights, 2014 & 2018

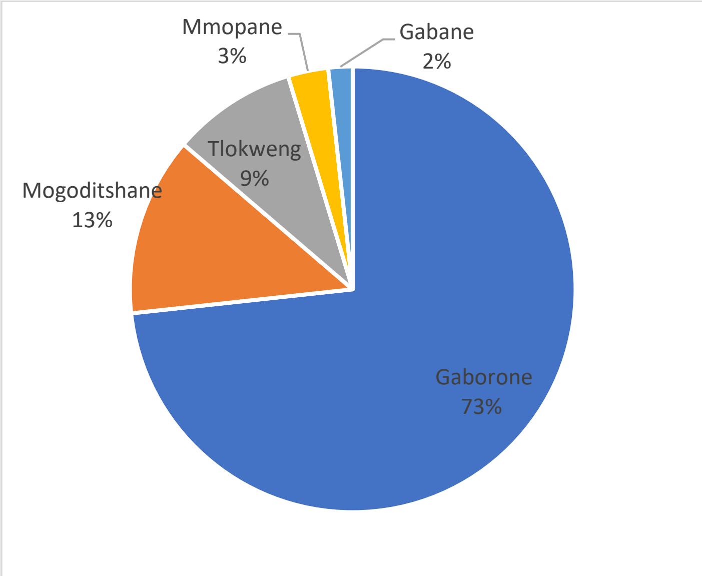


Source: own calculations

The sum of total nightlights is shared quite evenly across the three geographic categories (Figure 8). In 2014, Rural areas and Greater Gaborone accounted for 33% of nightlights each, whilst urban areas accounted for 34%. By 2018, the shares of nightlights were quite similar, although with a few changes. Rural areas produced 37% of nightlights, an increase of 4 percentage points; this is to be expected as the electrification of new rural areas will lead to an increase in nightlights produced within this classification. The share of nightlights produced by urban villages decreased marginally to 33%, along with a decrease in the share of nightlights produced within the Greater Gaborone region, to 30%.

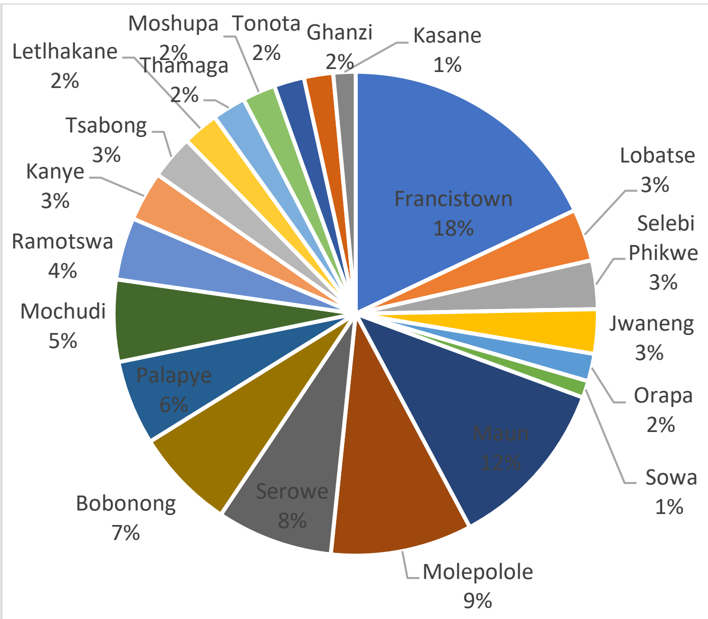
We can also consider the distribution of night lights within each of these categories. Within Greater Gaborone, Gaborone City held the largest share of nightlights, producing 73%. This was followed by Mogoditshane which produced 13% and Tlokweng which accounted for 9%. These results are consistent with the population differences between the two villages. Mmopane and Gabane respectively produced 3% and 2% of all nightlights within the region, which was to be expected given how relatively small they are in population.

Figure 9: Distribution of nightlights, Greater Gaborone (2018)



Amongst other urban areas, Francistown accounts for 18% of all nightlights (Figure 10). This is not surprising as it is the largest settlement and the central hub of business activity in the northern Botswana. The second greatest contributor of nightlights is Maun with 12%, which reflects the government and tourist activities that takes place in Maun. The two major mining towns, namely Jwaneng and Orapa contributed 3% and 2% of all urban area nightlights. This probably reflects that the mines themselves are located outside of the relevant urban areas.

Figure 10: Distribution of nightlights (2018), urban areas outside of Gaborone

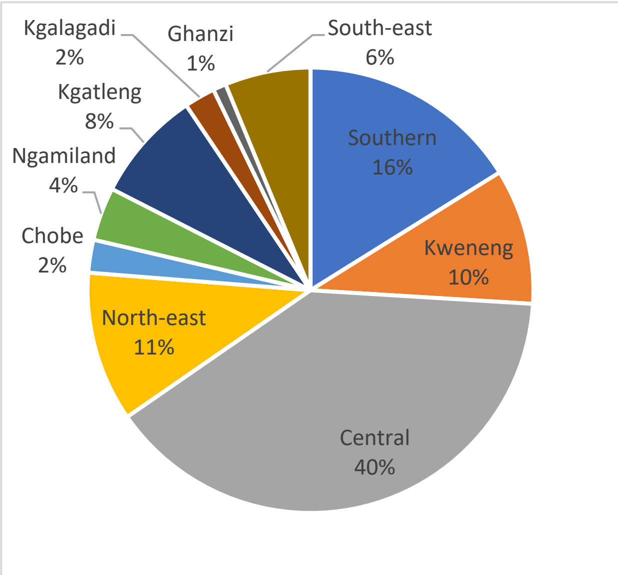


Source: authors

The Central District was responsible for 40% of all nightlights produced by rural settlements in Botswana. This is not surprising given the large size of the district and the proximity of these rural settlements to larger, fast growing towns such as Palapye and Serowe. It also includes several diamond mines (Orapa, Karowe and Damtshaa). The second largest contributor was the Southern District. It was accountable for 16% of all rural settlement nightlights, quite like the North-east and Kweneng districts which contributed 11% and 10% respectively. The reason why the rural settlements in the Southern district fared better could be because they lay within the out-of-town-commute range of Gaborone which would result in individuals who work in the city living there and subsequently producing nightlights. It also includes the Jwaneng diamond mine.

The Ghanzi and Kgalagadi districts contributed only 1% and 2% of all rural nightlights respectively; these districts are sparsely populated the regions are and far from larger towns/cities.

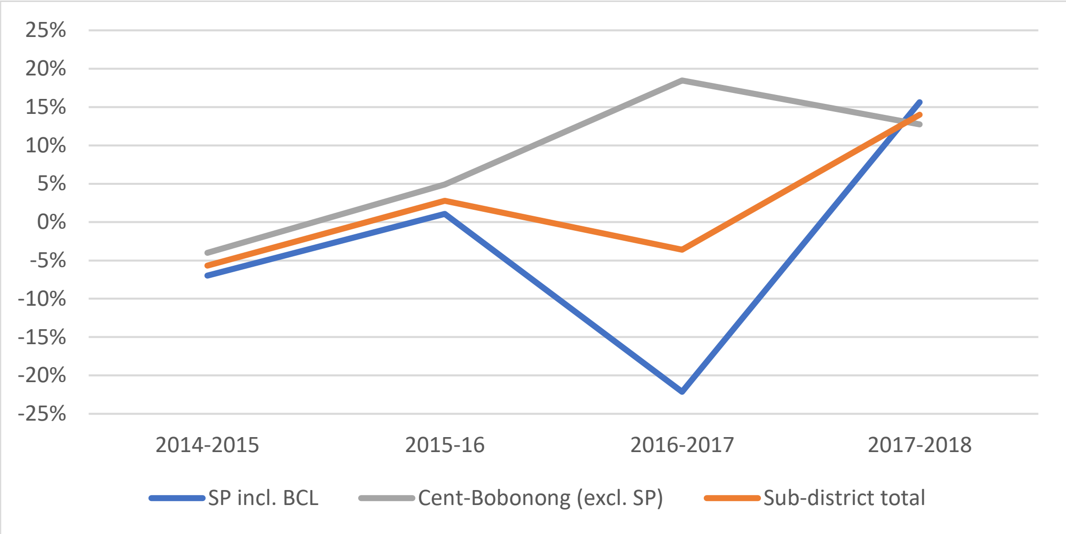
Figure 11: Distribution of nightlights (2018), districts outside of major urban areas



4.2.4 What do the nightlights data tell us about the impact of the closure of BCL?

One of the objectives of this work was to investigate, using nightlights, the impact of the closure of BCL on the economy of Selebi-Phikwe and the surrounding area. This is not as easy as originally anticipated, as the annual NL data is subject to considerable volatility (hence the use of annual averages above). For this analysis we have combined the NL data on Selebi-Phikwe town and the BCL mining area, and separated this from the rest of the Central – Bobonong sub-district. The figures used are for the 12 months periods from October to September the following year (2017), reflecting the timing of the BCL closure in October 2016. The following tentative conclusions can be drawn.

Figure 12: Annual change in night lights, Central – Bobonong sub-district and Selebi-Phikwe



As Figure 12 shows, Selebi-Phikwe suffered a major decline in NL in 2016-17, which reflects the year following the closure of the BCL mine in October 2016. Night lights fell by 22%, which would translate to a 14% decline in the town's NMGDP in 2017 based on the national elasticity parameter used in this study. The decline is in line with expectations at least in terms of direction, although possibly smaller than might have been anticipated in terms of magnitude.

However, there are two other interesting results. The first is that the decline was short-lived, and 2017-18 saw fairly strong growth, with a 16% increase in night lights, indicating that there was some recovery in the Selebi-Phikwe economy in that year. Secondly, the negative impact does not appear to have extended to the wider regional economy; in fact, the wider Central – Bobonong sub-district (excluding Selebi-Phikwe) experienced night lights growth of 18% in 2016-17, and 13% in 2017-18, suggesting a buoyant regional economy. A possible explanation of this is that miners retrenched from the BCL mine left the town of Selebi-Phikwe and returned to their home villages in the region, and added to economic activity there.

4.2.5 Share of economic lights by selected protected areas

Botswana is well known for its conservation efforts, and it has reserved a significant part of its land for conservation. The area set aside include Game Reserves and National Parks[18]. The Ministry of Environment, Wildlife and Tourism revised Wildlife Conservation Policy (MEWT, 2007) states that Protected Areas (PAs) should not just be used for conservation, but they should also be both for conservation and economic use in which both the private sector and adjacent communities are involved and benefit.

Therefore, we used night lights to track economic activity (from 2014 to 2018) for PAs in Botswana. Table 2 shows the share of nightlights by three PAs in Botswana. Six PAs were considered for analysis being, Khutse Game Reserve, Gemsbok Game Reserve, Central Kalahari Game Reserve (CKGR),

[18] Wildlife Management Areas have been excluded from the analysis

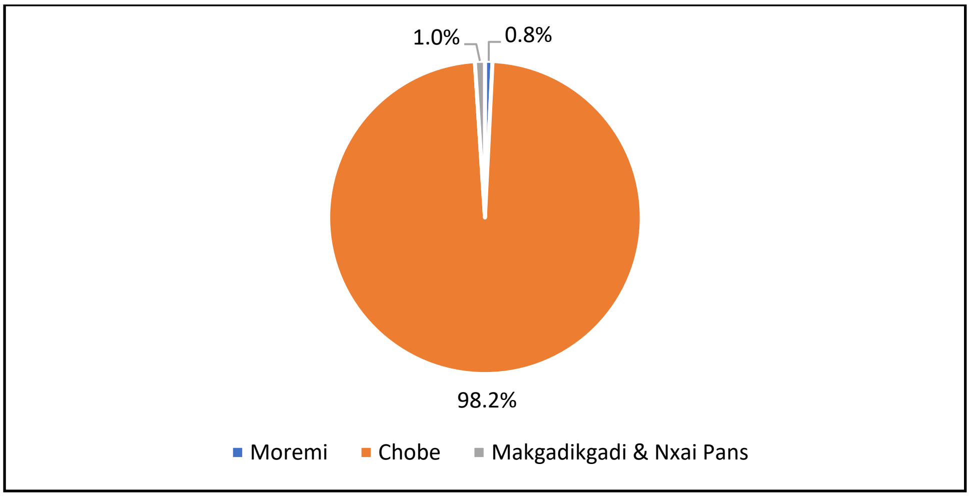
Makgadikgadi and Nxai Pans National Park, Moremi Game Reserve, Chobe National Park. Further analysis has not been carried out for the CKGR due to the presence of mining and hence its light intensity may not be a reflection of economic activities associated with PAs. The Khutse and the Gemsbok have no economic lights from 2014 to 2018 indicating a lack or no economic activity inside the PAs. Therefore, the nightlights results are presented for Moremi, Chobe and Makgadikgadi and Nxai Pans. There is an indication of economic activity for the three PAs. The presence of lodges and camps and visitations produce economic lights for the three PAs. The results indicate that Chobe has the highest economic activity (or highest light intensity[19]) amongst the selected PAs at 97.7% and 97.0% for 2014 and 2018 respectively. Chobe is the only PA that has a fully-fledged hotel (Chobe Game Lodge) operating within its boundaries. In addition, Chobe borders with Kasane township. Chobe National Park is also regarded as one of the priority areas for tourism due to its large number of elephants and the Chobe river front. This PA is also near the Victoria Falls in Zimbabwe (around 80km) and Livingstone in Zambia and the Caprivi Strip in Namibia. The area is therefore of great interest to visitors.

Table 2: Percentage share of nightlights by PAs, 2014-2018

	2014	2015	2016	2017	2018
Moremi Game Reserve	0.2%	0.3%	0.6%	1.2%	1.6%
Chobe Game Reserve	97.7%	99.5%	99.0%	97.8%	97.0%
Makgadikgadi and Nxai Pan	2.1%	0.2%	0.4%	1.0%	1.4%

On average (2014 to 2018), the Makgadikgadi and Nxai pans has the second highest share at 1% and Moremi has the lowest at 0.8% (see figure 13). However, it is important to note that the Moremi lights are higher than the Makgadikgadi lights from 2015 to 2018. The difference in the intensities may be attributed to the frequency of visitations or the amount and type of lights within the PAs. In the PAs scenario, there may be instances where intensity may be a true reflection of amount of economic activity . For example, Moremi GR is within a high value land in the delta with high-value camps). It is best to identify which PAs are likely to be homogenous and compare.

Figure 13: Average percentage share of nightlights by selected PAs, 2014 to 2018



[19] *The area has developed their lights over the period of 12 months or it is frequently lit on a monthly basis.*

5 Conclusions

The overall objective of this study is to use nightlight intensity to track economic activity in Botswana, and in particular to track economic activity at a geographically disaggregated level. The study found a strong association between the nightlights and NMGDP at the national level. This means that, nightlights are able to track economic activity at the national level well and could be used to predict annual GDP growth. The study showed a correlation of around 97% percent between the annual growth rates of nightlights and NMGDP.

The investigation also shows up some important results at the sub-national level (districts and key cities/towns/villages). As measured by nightlights, greater Gaborone accounts for 30% of economic activity, with other major urban areas accounting for one third of economic activity. The remaining areas account for 37%.

There are also important differences in the growth rates across settlements and settlement types. Firstly, growth as measured by night lights is higher in "rural" areas, followed by large urban villages, and finally cities and towns. This may reflect rural electrification, as well as the more general impact of infrastructure development and poverty alleviation policies across the country. Another factor is that most cities and towns are physically constrained by administrative boundaries, and therefore some of the 'city/ town' growth may occur in surrounding areas. This is illustrated by the fact that some of the highest growth rates are for urban villages and "rural" areas around Gaborone. This would be positive in terms of spreading economic activity around the country, especially as there are several areas enjoying robust growth that have nothing to do with Gaborone.

However, results show that despite the high association between NMGDP and nightlights at the national level, there are serious limitations at the subnational level. First, there is a higher annual variability of predicted NMGDP at the subnational level. The variability cannot easily be explained but could be attributable to the difficulties in measuring nightlights in a large, sparsely populated country. Other studies also have experienced this problem with nightlights at the subnational level (e.g. Prakash and Shukla 2019). Therefore, precaution should be taken when using nightlights to estimate economic activity at the subnational level. In time, nightlights can still play an important role in economic analysis, addressing issues such as urbanisation, regional income levels, population growth and migration, and the impact of policy and economic shocks at the national and subnational level, etc.

Further work is required to better understand the relationship between nightlights and economic activity at the sub-national level, and to understand the variability of sub-national night lights data. A key issue to be addressed is whether the night lights data are under-predicting economic activity in the larger urban areas, which have shown lower growth rates in this study. While there are no GDP data available at sub-national level, there may be other indicators of economic activity that could help in understanding this relationship. A new, continuous, household multi-topic survey has recently been introduced, which may – in time - assist here. A review of the data cleaning process could also help with addressing the data variability issue. Further work is also needed on the relationship between night lights and national GDP on a quarterly rather than an annual basis.

In terms of future work, the analysis could be productively repeated in a few years (e.g. 2 to 5 years). NL time series analysis could be used during the preparation of next national and district development plans. This would have the advantage of analysing a longer VIIRS NL data series. It should also be possible to obtain the EA shape files used for the 2021 Population and Housing Census, which would provide updated settlement information.

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Appendix

A1: 2001 & 2011 population figures and annual growth rates (2001 to 2011) for urban settlements in Botswana

	2001	2011	2001-11 growth rate
Molepolole	54,561	66,466	2.0%
Maun	43,776	60,273	3.2%
Mogoditshane	32,843	58,079	5.9%
Serowe	42,444	50,820	1.8%
Selibe-Phikwe	49,800	49,411	-0.1%
Kanye	40,628	47,013	1.5%
Mochudi	36,962	46,914	2.4%
Mahalapye	39,719	46,409	1.6%
Palapye	26,293	37,256	3.5%
Tlokweng	21,133	36,326	5.6%
Ramotswa	20,680	28,952	3.4%
Letlhakane	14,962	22,948	4.4%
Thamaga	18,117	21,471	1.7%
Tonota	15,617	21,031	3.0%
Moshupa	16,922	20,016	1.7%
Bobonong	14,622	19,389	2.9%
Mmopane	3,512	15,450	16.0%
Gabane	10,399	15,237	3.9%
Ghanzi	9,934	14,809	4.1%
Kasane	7,638	9,084	1.7%
Tsabong	6,591	8,945	3.1%

Source: Statistics Botswana (2015)

A2: 2001 & 2011 population figures and annual growth rates (2001 to 2011) for urban settlements in Botswana

	2001	2011	2001-11 growth rate
Gaborone	186,000	231,626	2.2%
Francistown	83,000	98,963	1.8%

Lobatse	29,700	29,007	-0.2%
Jwaneng	15,200	18,016	1.7%
Orapa	9,200	9,538	0.4%
Sowa	2,900	3,598	2.18%

A3: Sum of nightlights (in pixel values) for selected PAs, 2014 to 2018

PA	2014	2015	2016	2017	2018
CKGR	59.4	52.8	75.7	79.7	58.6
Chobe	35.1	43.0	45.4	50.2	48.9
Makgadikgadi & Nxai Pans	0.8	0.1	0.2	0.5	0.7
Moremi	0.1	0.1	0.3	0.6	0.8
Khutse	-	-	-	-	-
Gemsbok	-	-	-	-	-
Total	95.3	96.0	121.5	131.1	109.0

Note: CKGR has mining activities and the light intensity includes mining lights