WPS7461

Policy Research Working Paper 7461

Bright Lights, Big Cities

Measuring National and Subnational Economic Growth in Africa from Outer Space, with an Application to Kenya and Rwanda

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October 2015

Abstract

This paper uses the night lights (satellite imagery from outer space) approach to estimate growth in and levels of subnational 2013 gross domestic product for 47 counties in Kenya and 30 districts in Rwanda. Estimating subnational gross domestic product is consequential for three reasons. First, there is strong policy interest in how growth can occur in different parts of countries, so that communities can share in national prosperity and not get left behind. Second, subnational entities want to understand how they stack up against their neighbors and competitors, and how much they contribute to national gross domestic product. Third, such information could help private investors to assess where to undertake investments. Using night lights has the advantage of seeing a new and more accurate estimation of informal activity, and being independent of official data. However, the approach may underestimate economic activity in sectors that are largely unlit notably agriculture. For Kenya, the results of the analysis affirm that Nairobi County is the largest contributor to national gross domestic product. However, at 13 percent, this contribution is lower than commonly thought. For Rwanda, the three districts of Kigali account for 40 percent of national gross domestic product, underscoring the lower scale of economic activity in the rest of the country. To get a composite picture of subnational economic activity, especially in the context of rapidly improving official statistics in Kenya and Rwanda, it is important to estimate subnational gross domestic product using standard approaches (production, expenditure, income).

This paper is a joint product of the Kenya and Rwanda Country Management Unit, Macroeconomics and Fiscal Management Global Practice Group, and Poverty Global Practice Group. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at asanghi@worldbank.org.

Bright Lights, Big Cities: Measuring National and Subnational Economic Growth in Africa from Outer Space, with an Application to Kenya and Rwanda

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1. Introduction

In recent years, the intensity of night lights as measured from space has increasingly been used to estimate economic activity. The use of night lights as a proxy for economic activity rests on the assumption that as almost all consumption and investment activities in the evening or night require lighting, the intensity of night lights (or its growth over time) can be used as a proxy for the intensity of economic activity (or economic growth). Data on night lights have been used to estimate, among others, subnational income per capita (Ebener and others, 2005), the size of the informal economy in India (Gosh and others, 2010a), the global distribution of economic activity (Gosh and others, 2010b), the global incidence of poverty (Elvidge and others, 2009), and economic growth (Henderson, Storeygard and Weil, 2012).

One of the appealing features of night lights data is their availability on every level. Night lights data are measured on the so-called 30 arc sec level, corresponding to roughly 1 square kilometer at the equator. This means that night lights data can be used to estimate economic activity at levels that are not usually captured in national accounts, such as subnational administrative units (provinces, districts, counties, cities, etc.) or regions not coinciding with national borders (coastal vs inland regions, connected vs unconnected regions, etc.). For instance, Henderson, Storeygard and Weil (henceforth HSW) estimate, counter to intuition, that coastal areas in Sub-Saharan Africa are growing slower than the hinterland.

In this paper, we replicate the analysis by HSW but focus only on countries in Sub-Saharan Africa and use a slightly longer time-series (1992-2012 instead of 1992-2008). In line with HSW, we find a strong and robust link between growth in night lights and growth in GDP, with GDP estimated based on lights closely following GDP as measured from national accounts, for most countries in most years. We apply the results to estimate subnational growth in Kenya and Rwanda, two countries that are increasingly devolving powers to decentralized units. To our knowledge, this is the first time such an approach has been attempted to estimate GDP growth and levels for subnational units for Kenya and Rwanda.

We emphasize the fact that estimating subnational economic activity is more than solely an inquisitive exercise. This is because in the context of decentralized settings, there is a strong policy interest in seeking to see how growth can occur in different parts of countries, so that communities can share in national prosperity and do not get left behind. Second, subnational entities may themselves may want to know and understand how they stack up against their neighbors and competitors, and how much they contribute to national GDP. Third, such information would help private investors who shop around for viable investment destinations to assess more accurately where to undertake investments. Incidentally, countries that have decentralized may consider including subnational GDP as one possible criteria that could determine how funds transferred from the national government are shared among subnational governments. If and when that were to happen, then subnational entities stand to gain or lose depending on their contribution to national GDP. This can have ramifications -- for example, one oft-cited “fact” in the case of Kenya is that Nairobi contributes over 60% of Kenya’s GDP (Kenya Urban Areas Brief 2013). However, our indicative results show that Nairobi’s contribution to national 2013 GDP, though still the highest, stood at 13%. It bears emphasizing that our results come with caveats, in particular, underestimating agriculture’s contribution to county level GDP, as detailed in the paper.

In addition to affecting how including county-level GDP in the revenue sharing formula, in the case of Kenya, can considerably affect resource allocation among individual counties, estimating subnational economic activity also has other uses. For one, counties themselves may want to know and understand what drives growth within their borders, and how they stack up against others. And another important reason is that, with a better understanding of county-level growth dynamics, such information would help private investors assess more accurately where to undertake private investments.

This paper proceeds as follows: The next section summarizes the data and sketches the relationship between nightlights and GDP using observations from the sample. Section 3 specifies the empirical model and presents the main results. Section 4 applies the model estimates to subnational GDP growth in Kenya and Rwanda, while section 5 focuses on subnational GDP levels. The final section concludes.

2. The Link between Night Lights and GDP

2.1 Data

Data on night lights are provided by the Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS). The DMSP satellites circle the earth 14 times a day and record the intensity of Earth-based lights. The data picked up by the satellites have been digitized since 1992. We used stable light imagery of SSA derived from scores of orbits of the DMSP OLS in from 1992-2013 since this product inter-calibrated where fires and other ephemeral lights have been removed, although there are noteworthy blunders associated with over-glow effects where lighting spreads to neighboring pixels (and hence economic activity is wrongfully attributed to certain places). The stable lights imagery has annual quantized pixels with values (Digital Numbers) with integers ranging from 0 to 63. This product is optimal especially for SSA where ephemeral lighting is minimal during the night where gas flares are a rare phenomenon. Gas flares are combustion devices used mainly in oil wells and big offshore platforms to burn flammable gas (mostly methane) released during the operations of oil extraction.

There are other satellite sensors of the same resolution and scale but not appropriate for economic activity studies. Landsat, for instance, depicts settlement expansion, but is not available for frequent temporal coverage.

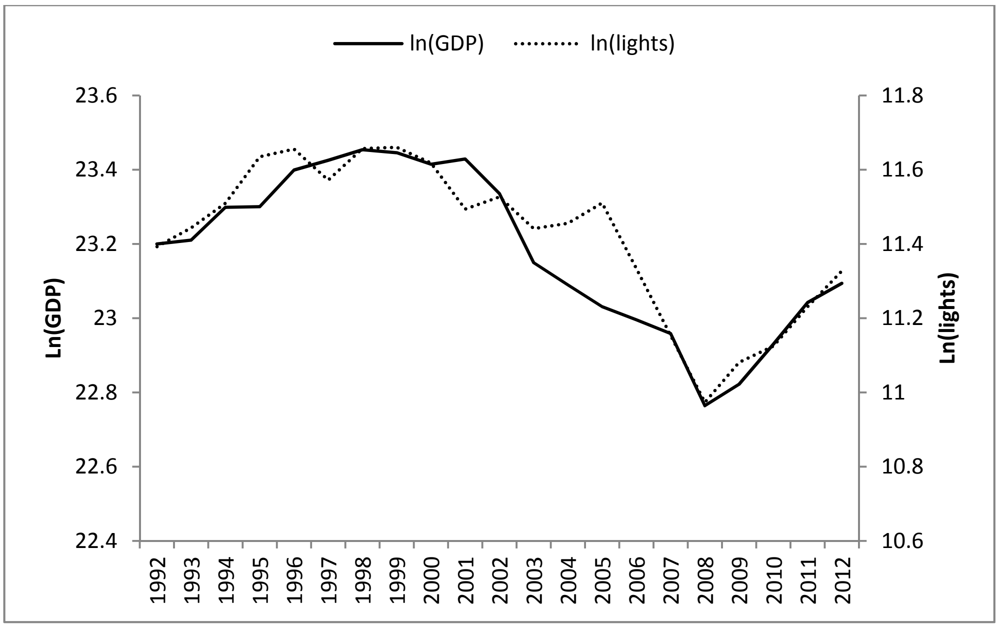
Data on GDP and other indicators used in the analysis (surface of country territory, electricity consumption, etc.) are provided by the World Development Indicators (2014). Following HSW, we use constant GDP in local currency units.

Night lights data are available for all 47 Sub-Saharan African countries between 1992 and 2012, resulting in 987 country-year observations. South Sudan is not included since it only became an independent country in 2011. GDP data are not available for Somalia, resulting in a final sample of 966 country-year observations.

2.2 Night lights and GDP

HSW provide illustrative examples of the link between night lights and economic or political events by focusing on the Asian financial crisis and changes in night lights in Indonesia, the difference between the two Koreas, and the Rwandan genocide. Our sample includes many more salient examples. The intensity of night lights closely tracks Zimbabwe's economic decline between 2000 and 2008, when real GDP contracted by almost 50 percent (Figure 1). When GDP growth finally turned positive again after 2008, the intensity of night lights also reversed its declining trend. On the other extreme, Equatorial Guinea's phenomenal growth following the discovery of vast amounts of oil (per capita GDP increased 27-fold between 1992 and 2012) is reflected in the strong growth in night lights over the same period (Figure 2).[2]

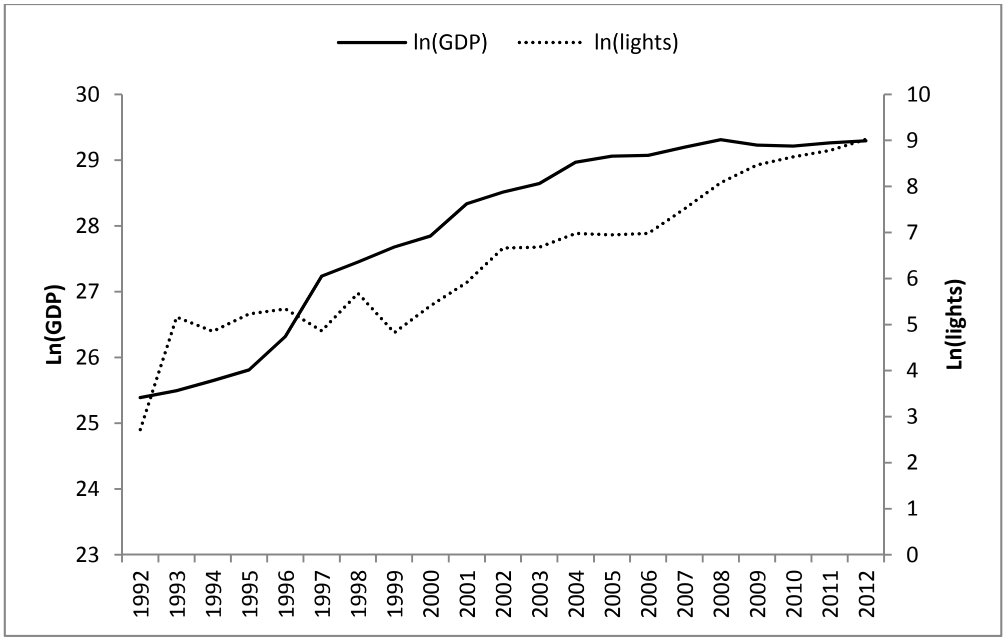
Figure 1: Zimbabwe's economic decline



Source: WDI (2014) and NGDC (2014). Authors' calculations

Figure 2: Equatorial Guinea's growth

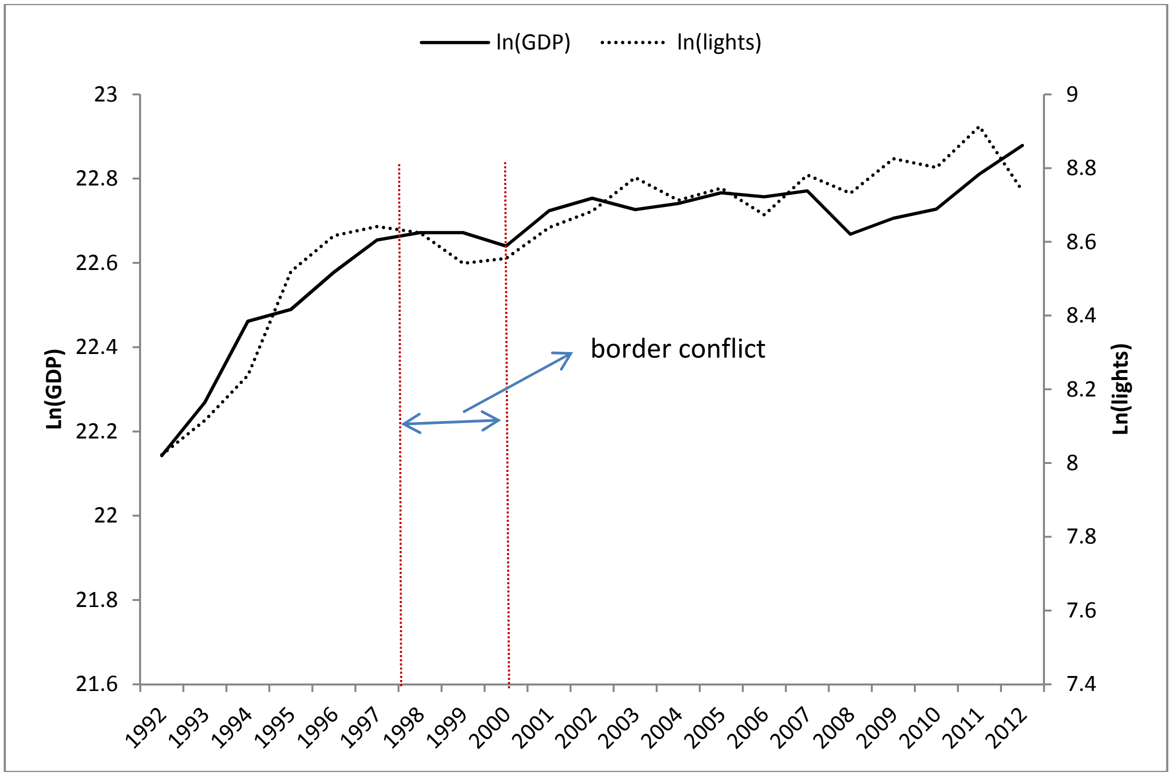
[2] Despite the 27-fold increase in per capita GDP, poverty was estimated at 77 percent in 2006 (based on national poverty line).



Source: WDI (2014) and NGDC (2014). Authors' calculations

One can argue that the close relationship between GDP and night lights illustrated in Figures 1 and 2 is due to the sheer magnitude of the events. After all, we would expect the intensity of lighting to respond to a halving of the economy (Zimbabwe) or a 27-fold increase of it (Equatorial Guinea). Night lights however also seem to respond to events that impact economic activity to a far lesser extent. To illustrate, take the Eritrean-Ethiopian border conflict of 1998-2000. While for a country the size of Ethiopia the localized border conflict did not have a discernible impact on the economy, GDP in Eritrea, a small country with less than four million inhabitants at the time, contracted by 6 percent during the conflict. The intensity of night lights reacted to the temporary contraction in GDP between 1998 and 2000, and picked up again after 2000 with renewed economic growth (Figure 3).

Figure 3: The Ethiopian-Eritrean border war and night lights in Eritrea



Source: WDI (2014) and NGDC (2014). Authors' calculations. Vertical lines demarcate the border war period.

Overall, the average annual growth in GDP for the 46 countries in our sample amounted to 4.4 percent, a little lower than the annual growth in lights (4.8 percent). The three countries that recorded the slowest GDP growth between 1992 and 2012 (Zimbabwe, Burundi, and DRC) are also among the countries with the slowest growth in night lights (Table 1). The countries with the fastest-growing economies (Cape Verde, Liberia, and Equatorial Guinea) also experienced fast growth in night lights as measured from space. Overall, there is a strong positive relationship between changes in lights and changes in GDP in the sample of Sub-Saharan African countries (Figure 4).[3]

Table 1: Annual GDP growth and night lights for fast-and slow-growing countries

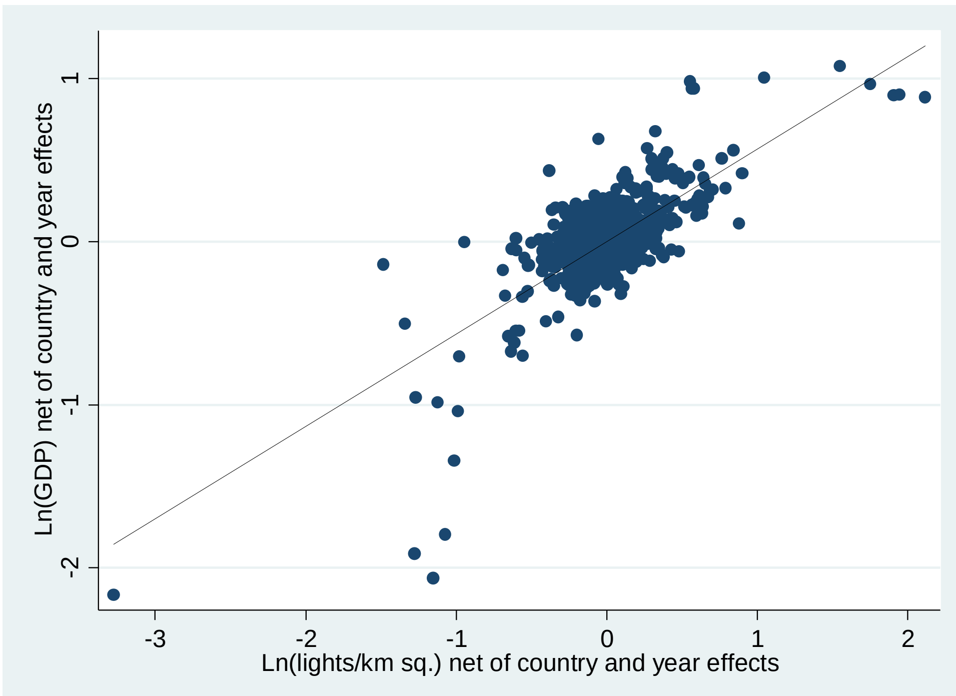
	Annual GDP growth (1992-2012)	Annual lights growth (1992-2012)
Countries with slowest growth		
Zimbabwe	-0.5	-0.3
Burundi	0.7	2.5
DRC	1.1	2.2
Countries with fastest growth		
Cape Verde	8.2	5.5
Liberia	9.0	12.1
Equatorial Guinea	21.5	37.0

[3] This is net of country and year effects.

Sample average	**4.4**	**4.8**

Source: WDI (2014) and NGDC (2014). Authors' calculations.

Figure 4: GDP and lights in Sub Sahara Africa



Source: WDI (2014) and NGDC (2014). Authors' calculations. 966 observations.

3. Methods and Results

3.1 Statistical specifications

We use the same specifications as HSW to estimate GDP based on night lights, focusing on growth formulations. The first specification is a fixed effects specification using the full sample and can be written as:

$$Ln(GDP_{i,t}) = \alpha + \beta \ln\left(lights_{i,t}\right) + C_i + \varphi_t + \varepsilon_{i,t} \qquad (1)$$

With $Ln(GDP_{i,t})$ being the natural log of GDP of country *i* in year *t* (in constant local currency units), $\ln\left(lights_{i,t}\right)$ the natural log of lights per km² in country *i* in year *t*, C_i the country fixed-effects, and φ_t the year fixed-effects. The year fixed-effects control for differences in light sensitivity across the different satellites and also for changes in economic conditions and lighting technology. Lights per km² is calculated as the sum of lights in a country in a given year divided by the country's total surface. Identification in specification (1) comes from within-country variation in lights and GDP over time, relating growth in lights within countries to growth in GDP.

The second specification adds a country-specific time trend to specification (1) to examine the extent to which fluctuations around a country's growth path can be explained by lights. This specification focuses on annual fluctuations in GDP and can be written as:

$$Ln(GDP_{i,t}) = \alpha + \beta \ln\left(lights_{i,t}\right) + \mathrm{C}_i + \varphi_t + (\mathrm{C}_i * \varphi_t) + \varepsilon_{i,t} \quad (2)$$

Where $(\mathrm{C}_i * \varphi_t)$ is the country-specific time-trend (the interaction between the country and year fixed effects. The third specification, still following HSW, estimates (1) in differenced form to focus on long-term growth between 1992 and 2012 and can be written as:

$$\Delta GDP_{i,2012-1992} = \alpha + \beta\, \Delta\left(lights_{i,2012-1992}\right) + \varepsilon_{i,t} \quad (3)$$

Where $\Delta GDP_{i,2012-1992}$ is GDP growth in country *i* between 1992 and 2012 and $\Delta\left(lights_{i,2012-1992}\right)$ growth in night lights in country *i* between 1992 and 2012. The (time-invariant) country fixed effects are swept out by the differenced form. We also estimate specification (3) for the shorter 2000-2012 period.

3.2 Results

Table 2 shows the results for a balanced panel of 46 countries over 21 years. Column (1) estimates specification (1) with country and year fixed effects. We find a β of *0.57*, meaning that a 1 percent increase in night lights is associated with a 0.57 percent increase in GDP, controlling for the country and the year. The coefficient is highly statistically significant and twice as large as the coefficient estimated in HSW (*0.28* in a larger sample covering 188 countries and 17 years). The within-country R squared amounts to about 0.8.

Table 2: Baseline results (specification 1) – 46 SSA countries

	ln(GDP) (1)	ln(GDP) (2)	ln(GDP) (3)	ln(GDP) (4)
ln(lights/km²)	0.567***	0.323**		0.364**
	[0.064]	[0.134]		[0.156]
ln(lights/km²) sq.		-0.034*		
		[0.017]		
ln (electricity consumption)			0.365***	0.231**
			[0.123]	[0.089]
Observations	966	966	425	425
Countries	46	46	22	22
R sq. (within)	0.797	0.804	0.799	0.83

Notes: Dependent variable is the natural log of GDP in constant LCU. All specifications include country and year fixed effects. Robust standard errors clustered by countries in brackets. ***: significant at 1%-level; **: significant at 5%-level; *: significant at 10%-level. Data source: NGDC (2014) and WDI (2014).

In Column (2) we test whether there is a quadratic relation between lights and GDP. In contrast to HSW, we find a modest and weakly significant quadratic relation in our sample, with the association between lights and GDP being weakly concave. This quadratic specification is however not robust to different sample definitions and is in large part driven by Equatorial Guinea. Between 2006 and 2012, lights in Equatorial Guinea grew significantly faster than GDP (see Figure **2**), introducing a mild quadratic relation in the overall sample. The quadratic relation disappears when Equatorial Guinea is dropped from the sample (21 observations dropped from the total of 966). Given that the quadratic specification is not robust, we proceed with the linear specification in further analysis.

In Column (3) we replace lights observed from space by data on electrical power consumption (in kilowatt hours, obtained from the World Development Indicators). As data on electricity consumption are only available for 22 countries in SSA, the number of observations drops from 966 to 425 (not all 22 countries have data for all 21 years). We find a strong and statistically significant association between electricity consumption and GDP in the reduced sample (elasticity of *0.37*). The coefficient is however considerably smaller than the one estimated between night lights and GDP (*0.58*). This may potentially be explained by the relatively high use of generators in SSA, where power outages on the main grid are frequent. WDI data on electricity consumption only encompass output from power plants and hence may underestimate the intensity and volume of night lights in countries with a strong reliance on private generators. Indeed, if we estimate a panel regression of log lights on the log of electricity consumption (with year fixed effects), we find that the within-country variation in electricity consumption explains “only” 64 percent of the variation of night lights as observed from space, hinting at the existence of other sources of lighting as well.

In the fourth column of Table 2 we include both electricity consumption and lighting as observed from space (for the 22 countries with data on electricity consumption). Similar to HSW, we find that both remain statistically significant, indicating that they may not capture the exact same underlying economic activity. The goodness of fit somewhat increases when including both electricity consumption and lights (within R-squared of *0.83* compared to *0.80* with lights alone – column (1)). The elasticity between lights and GDP (*0.36*) remains higher than the one between electricity consumption and GDP (*0.23*).

Table 3 explores the relation between night lights and two other types of GDP growth: Annual fluctuations about a country’s growth path (specification (2)) and long-term growth between 1992 and 2012 and 2000 and 2012 (specification (3)). Column (1) in Table 3 adds a country-specific time-trend so that lights now only explain fluctuations of GDP about a country’s longer-term growth path. The size of the coefficients falls to *0.11* (from *0.57*), but is still highly statistically significant, indicating that short-term fluctuations in GDP are picked up to some extent by changes in lights. The second column of Table 3 examines the within-country association between growth in GDP and growth in night lights between 1992 and 2012. In line with HSW, we find a strong and statistically significant association between long-term GDP growth and long-term lights growth. The long difference estimate of β amounts to *0.55,* similar to the fixed effect value of *0.57.* The R-squared remains high at 0.76, indicating that 76 percent of the within-country variation in GDP between 1992 and 2012 can be explained by the variation in night lights.

Table 3: Annual fluctuations and long-term growth – 46 SSA countries

	Country-specific time-trend	Long difference 2012-1992	Long difference 2012-2000
ln(lights/area)	0.114***	0.553***	0.357***
	[0.019]	[0.032]	[0.059]
Observations	966	46	46
Countries	46	46	46
R sq. (within)	0.911	0.764	0.484

Notes: Dependent variable is the natural log of GDP in constant LCU. All specifications include country and year fixed effects. Robust standard errors clustered by countries in brackets. ***: significant at 1%-level; **: significant at 5%-level; *: significant at 10%-level. Data source: NGDC (2014) and WDI (2014).

Finally, the last column in Table 3 estimates growth in GDP between 2000 and 2012 based on growth in night lights over the same period. While the association remains strong and statistically significant, the coefficient (*0.36*) is considerably lower than the one for the full period (*0.55*), suggesting that the association between night lights and GDP has become weaker over the past decade.

To summarize, we are able to replicate all HSW findings using a sample of 46 Sub-Saharan African countries and a 21-year time period (1992-2012). Compared to HSW, we find a stronger elasticity between night lights and GDP, which may perhaps be explained by the low level of development in SSA relative to the rest of the world. In rich and highly lit places of the world, an increase in GDP may not produce much more lighting. In poor and largely unlit places however, an increase in economic activity could have a larger impact on lighting.[4] In the preferred specification (specification (1)), a one percent increase in night lights is associated with a 0.57 percent increase in GDP, an effect strongly statistically significant.

How does the estimation method perform out of sample? Based on the growth of night lights in the whole of SSA, specification (3) (the long differenced form) estimates that real GDP in SSA increased by 3.2 percent per year between 1992 and 2012 and by 4 percent per year between 2000 and 2012. This substantially underestimates the national accounts based growth rates of 4.1 percent and 5 percent, respectively. The importance of agriculture in SSA could potentially be the reason for the underestimation. A substantial part of Africa's population is engaged in small-scale subsistence agriculture. Since this activity is largely unlit, one can argue that night lights only pick up economic activity in the secondary and tertiary sectors. The next section will elaborate on this.

What about the economy of Somalia? National accounts data for Somalia have been non-existing since 1991, when the country sunk into chaos following the toppling of the Badre regime. Somalia, still according to the long differenced form, grew by 4.8 percent per year between 1992 and 2012, with this however largely driven by a rebound effect following the heavy fighting of 1990-92

[4] HSW also find suggestive evidence of a lower elasticity between lights and GDP in high-income countries.

(night lights increased more than six-fold between 1992 and 1993). Focusing on a more recent period, growth in Somalia is estimated (based on night lights) at 4 percent per annum between 2000 and 2012.

3.3 The role of agriculture

In many countries in SSA, a large part of the population is engaged in small-scale subsistence agriculture. Since this activity is largely unlit, it will not show up in night lights. This means that estimating GDP *levels* in SSA based on night lights would likely result in an underestimation of "true" GDP. In Liberia for instance, agriculture accounted on average for 67 percent of GDP over the 1992-2012 period. Estimating Liberia's GDP based on night lights would fail to capture two-thirds of Liberia's economic activity. If growth in agriculture accounts for a sizable part of aggregate GDP *growth*, growth in night lights would also tend to underestimate GDP growth. In Rwanda for instance, agriculture accounts for about 25 percent of total GDP growth. Estimating growth based on nightlights would hence underestimate true growth.

To what extent does the importance of agriculture underestimate GDP growth? Linking the residuals of specification (1) to the share of agriculture in GDP, we find a positive but weak correlation. Countries where GDP growth is underestimated by nightlights have on average a higher share of agriculture in GDP (29.7 percent) than countries where GDP is overestimated (26.1 percent), though the difference is relatively small. In Table 4, we divide our sample into two based on whether the country has an above or below-average share of agriculture in GDP (average for the countries in the sample).

Table 4: Night lights and growth for more and less agrarian countries

	ln(GDP)	ln(GDP)
	Above average share of agriculture	Below average share of agriculture
ln(lights/area)	0.445***	0.656***
	[0.078]	[0.046]
Observations	525	441
Countries	25	21
R sq. (within)	0.851	0.781

Notes: Dependent variable is the natural log of GDP in constant LCU. All specifications include country and year fixed effects. Robust standard errors clustered by countries in brackets. ***: significant at 1%-level; **: significant at 5%-level; *: significant at 10%-level. Data source: NGDC (2014) and WDI (2014).

As expected, we find that the association between nightlights and GDP is stronger in countries where unlit agriculture accounts for a smaller part of overall economic activity (column (2) in table 4). In these countries, manufacturing and services account for the bulk of GDP, and growth in these sectors is more likely to turn up in lights. The association between nightlights and GDP remains however strongly significant for the agrarian countries as well.

The preceding discussion suggests that estimates of GDP growth based on nightlights could, at least for countries in SSA, be improved by controlling for the importance of agriculture in the economy. However, specifying a control variable for which national accounts or survey data is needed (such as the share of agriculture in GDP or the share of the population engaged in agriculture) would run counter to the purpose of this study, which is to see whether proxies such as nightlights can be used to estimate growth in areas (sub-national or supra-national) for which there are no national accounts or survey data. One option is to use rainfall or vegetation data, which share many of the desirable features of nightlights data, to proxy the performance of the agricultural sector. This is something to explore in future work.

4. Application to Kenya and Rwanda: GDP Growth

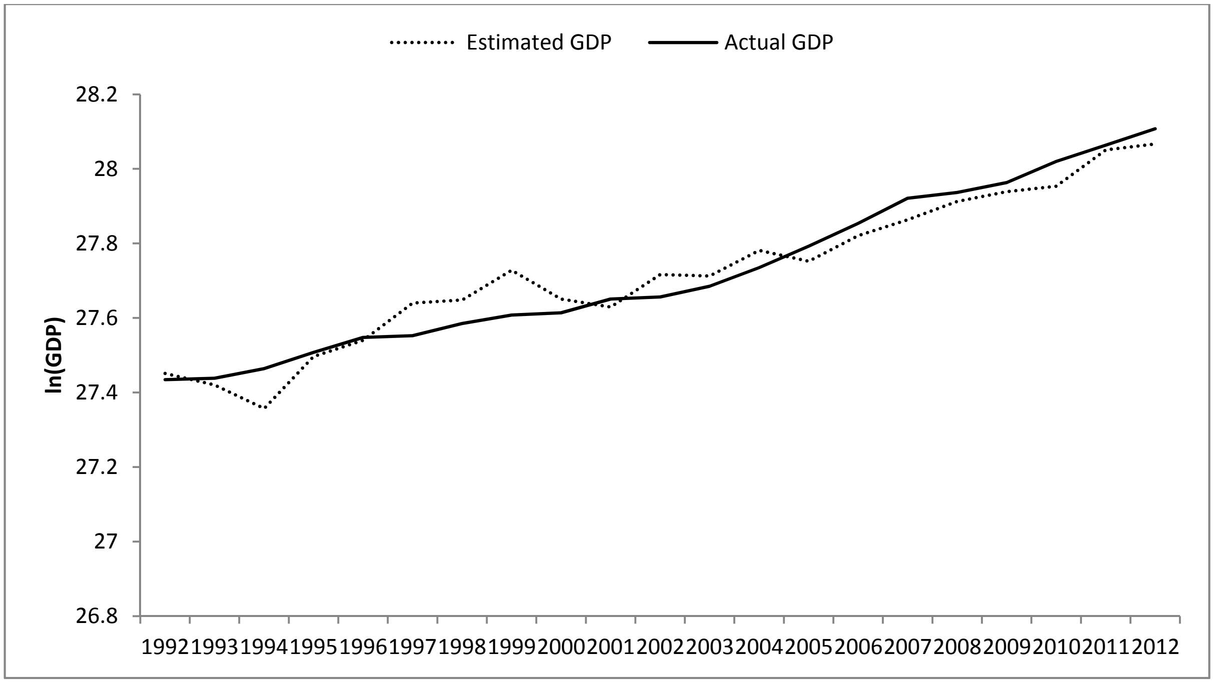
In this section we use the results from the long-differenced specification to estimate subnational GDP growth in Kenya and Rwanda based on the evolution of night lights.

4.1 Kenya

Kenya's 47 county governments came into existence at the March 2013 election. Transfer of staff and functions from around 280 de-concentrated district administrations and 175 local authorities was largely completed by January 2014 when counties took over management of payroll for all their staff. Funding for devolved functions is provided for through an unconditional equitable share, allocated among counties on the basis of a formula proposed by the Commission on Revenue Allocation and approved by the National Assembly in November 2012. The formula is due for revision after three years, and thereafter every five years. The formula incorporates four proxy measures of expenditure needs: population, equal shares (reflecting diseconomies of scale in smaller counties), poverty and land area. At present, the formula ignores the very different fiscal capacity between counties, particularly those in rural and urban areas. An important question for the future is whether to also include a measure of revenue-raising capacity, so as to achieve more effective equalization. To generate the right incentives for maximum fiscal effort by the county governments, such a component in the formula should be based on an objective measure of each county's potential to raise revenue, not how much is actually raised. In the absence of detailed information on the size of the tax base in each county, one approach might be to use county GDP as a proxy measure.

Focusing first on Kenya as a whole, how do night lights perform in predicting aggregate GDP growth? The short answer is: not too bad. For Kenya, GDP as predicted by night lights closely tracks GDP as measured by national accounts, in particular since the start of the 2000s (Figure **5**). Based on the growth of night lights and using the long differenced specification (last column of Table 3), we estimate an annual GDP growth of 4.0 percent between 2000 and 2012, slightly lower than the actual national-accounts based growth rate of 4.2 percent.

Figure 5: Estimated and measured GDP in Kenya

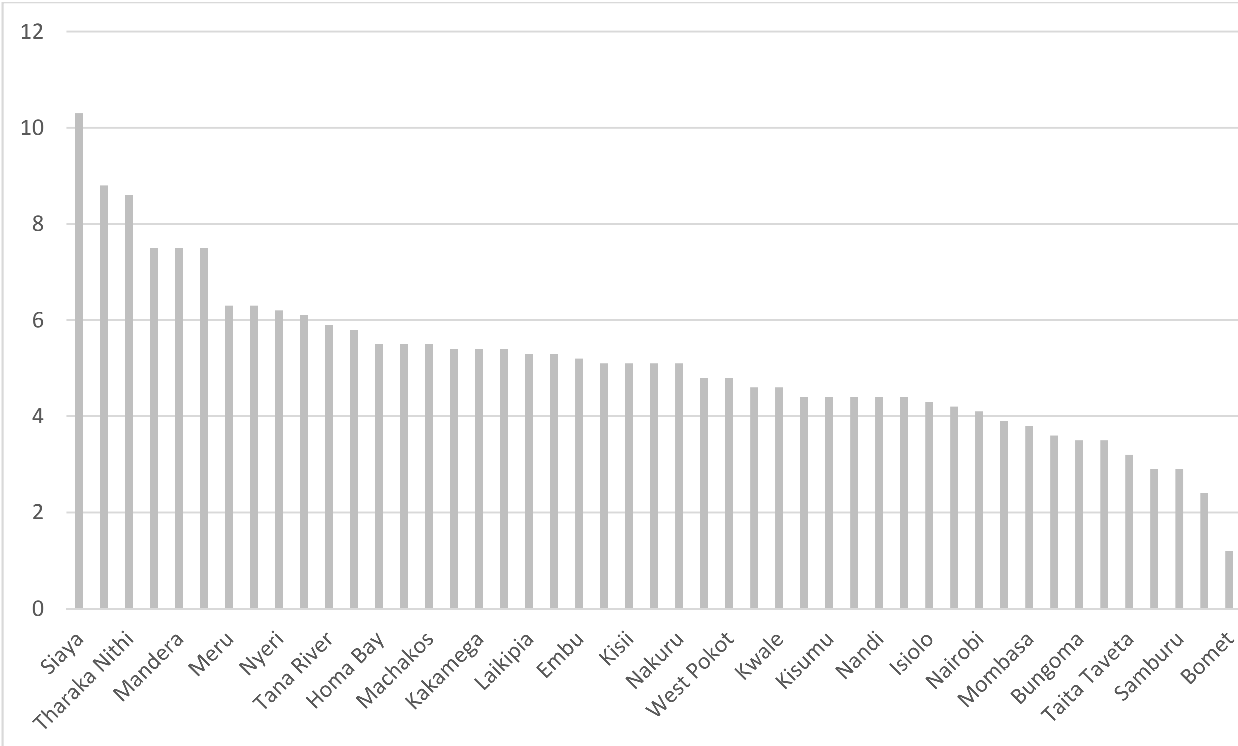


Source: WDI (2014) and NGDC (2014). Authors' calculations.

Estimating county-level GDP growth based on growth in county night lights since 2000, we find that the lakeside county of Siaya has grown fastest (estimated GDP growth of 10 percent per annum between 2000 and 2011), followed by Elgeyo Marakwet (8.8 percent per annum) and Tharaka Nithi (8.6 percent – see Figure 6). While these counties are still poor compared to the national average, the intensity of their night lights as picked up from space grew strongly since the turn of the century: The sum of lights seven-folded in Siaya and almost five-folded in Tharaka Nithi and Elgeyo Marakwet. At the other end, Bomet grew slowest of all counties (1.2 percent per annum), followed by Kericho (2.4 percent) and Marsabit (2.9 percent). Nairobi county grew at an estimated 4.1 percent and Mombasa at 3.8 percent. Based on night lights, Nakuru and Kisumu grew at 5.1 percent and 4.4 percent, respectively.[5]

Figure 6: Average annual county-level GDP growth in Kenya, 2000-2012 (%)

[5] Standards errors of the estimates are small and not shown in Figure 6.

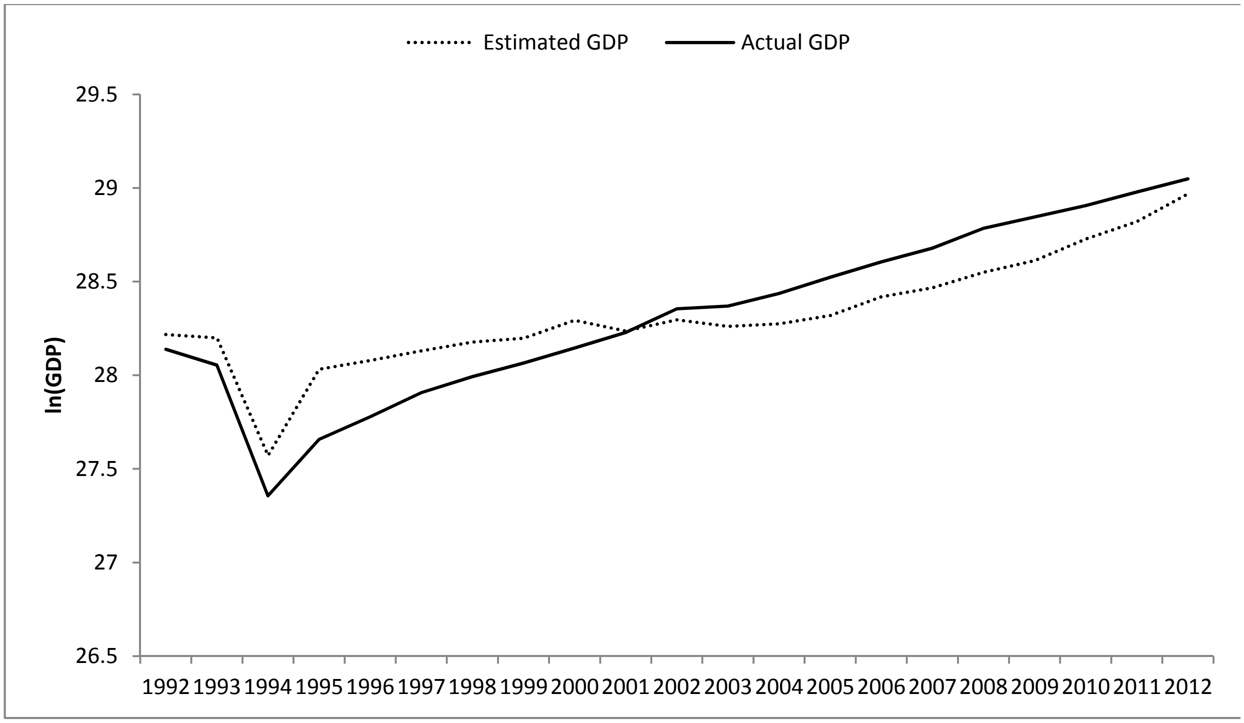


Notes: Based on long-differenced specification between 2000 and 2012

4.2 Rwanda

For Rwanda, nightlights-based GDP also tracks measured GDP, though the level of correspondence is lower than for Kenya (Figure 7). Night lights tend to substantially overestimate GDP up until the early 2000s, driven in particular by the rapid recovery of lights (compared to GDP) in the wake of the genocide. Growth in lights stagnated between 2000 and 2005, leading to an underestimation of GDP growth during this period. Based on night lights, we estimate an annual growth rate of 5.4 percent between 2000 and 2012, substantially lower than the national accounts-based true growth rate of 8 percent. This difference may potentially be explained by the relatively large importance of agriculture for the Rwandan economy: Between 2000 and 2012 agriculture accounted for about 2 percentage points of aggregate growth on a yearly basis. As agriculture is largely unlit, the part of growth accounted for by agriculture would not be picked up by nightlights.

Figure 7: Estimated and measured GDP in Rwanda

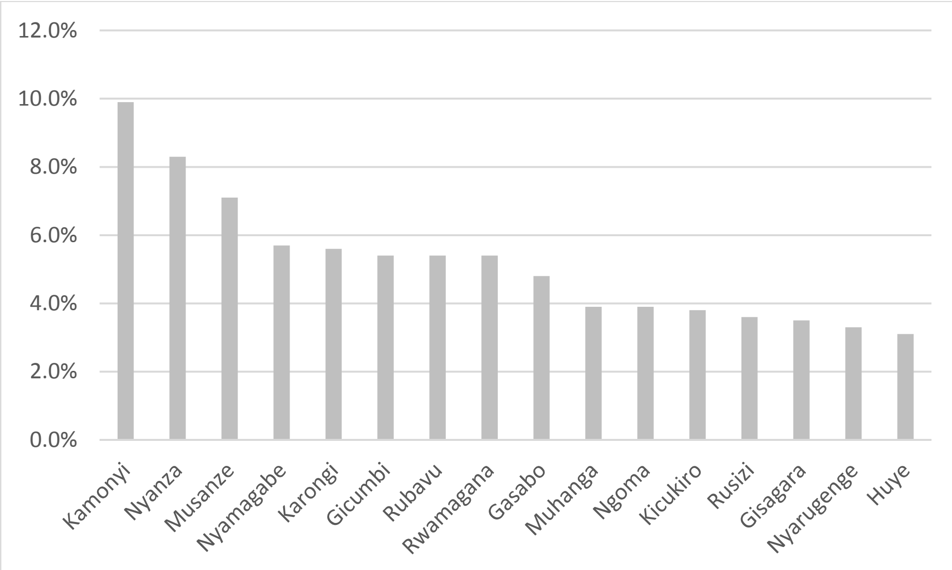


Source: WDI (2014) and NGDC (2014). Authors' calculations.

Since 2006, Rwanda is divided into 30 districts, which are the main service-delivery units. All household surveys are representative at the district level, but there is no information on district-level economic growth. Estimating district-level growth based on nightlights is however complicated by the low intensity of lights: Four districts did not emit any observable lights at all during 2000-2011, and ten districts only have nonzero observations towards the end of the 2000-2011 period. As a result, we can only estimate nighlights-based GDP growth for 16 districts.

Figure 8 shows estimated average GDP growth for the 16 districts with sufficient lighting. According to the estimates, Kamonyi, Nyanza, and Musanze districts grew fastest between 2000 and 2012, with annual growth rates of 9.9, 8.3, and 7.1 percent, respectively. Rubavu, Karongi, Gicumbi, Nyamagabe, and Rwamagana also grew at more than 5 percent per year. Within Kigali city, Gasabo district grew at 4.8 percent per year, Kicukiro at 3.8 percent, and Nyarugenge at 3.3 percent. The two slowest growing districts (among those with data) were Huye (3.1 percent) and Nyarugenge (3.3 percent).

Figure 8: Average annual district-level GDP growth in Rwanda, 2000-2012



Notes: Based on long-differenced specification between 2000 and 2012; Only nonzero lights data for 16 districts

5. Application to Kenya and Rwanda: GDP Levels

In this section we estimate subnational GDP levels for 2013 based on the spatial distribution of night lights and the rural population. Following Ghosh and others (2010), we assume that the within-country distribution of nightlights (across the subnational units) only proxies the within-country distribution of secondary- and tertiary sector economic activity (given that agriculture is largely subsistence and unlit). As such, the spatial distribution of nightlights within a country is used only to distribute the part of estimated GDP resulting from industrial and service activities. The part of estimated GDP accounted for by agriculture is distributed across the subnational units in proportion to their share of rural population.[6]

Our methodology consists of three steps. In the first step, we estimate national GDP based on specification (1). The estimated GDP is divided into two parts based on the share of agriculture in the economy (based on actual national accounts data): Agricultural GDP and industrial and services GDP. In the second step, we distribute industrial and services GDP among the subnational units in proportion to their share of national nightlights. In the third step, we distribute agricultural GDP among the subnational units in proportion to their share of the rural population (we assume that urban populations do not produce agricultural output). Finally, we sum estimated industrial and services GDP and estimated agricultural GDP to arrive at an estimate of subnational-level GDP.

[6] This is in contrast to Ghosh and others (2010) who use the Landscan data to distribute agricultural GDP among sub-units.

5.1 Kenya

Table 5 and Figure 10 show the county-level GDP estimates for Kenya. Based on specification (1), we estimate total 2013 GDP for Kenya at $26.8 billion (2005 USD), close to its actual level of $26.9 billion (WDI, 2014). On county-level, we find that Nairobi had the highest overall GDP in 2013 ($3.4 billion), followed by Kiambu ($3.0 billion), Nakuru ($2.3 billion), Nyeri ($1 billion), and Kilifi ($1 billion). Counties with the lowest GDP are the sparsely populated counties of Isiolo ($56 million), Lamu ($58 million), Samburu ($67 million), Elgeyo Marakwet ($108 million), and Tharaka Nithi ($109 million). Nairobi has the highest contribution to national GDP (13 percent), followed by Kiambu (11 percent), Nakuru (9 percent) and Nyeri (4 percent – see Figure 9).

When we control for population by looking at GDP per capita, there are substantial changes (Figure 11). Kiambu is the best-off county, with a per capita GDP of $1,785 (2005 USD), followed by Nyeri ($1,503), Kajiado (1,466), Nakuru ($1,413), and Kwale ($1,406). Due to its large population, Nairobi does not make it to the top five with an estimated per capita GDP of $1,081 (ranked 8th among the 47 counties, one spot in front of Mombasa). Note that Nairobi and Mombasa have zero agricultural GDP because the 2009 census classified these counties as 100 percent urban. This may underestimate their GDP if agricultural activity does take place in these counties.

Table 5: Estimates of County-Level GDP in Kenya, 2013 (in constant 2005 USD).

County	Sum of lights	Secondary and tertiary-sector GDP (2005 USD)	Agricultural GDP (2005 USD)	Total GDP (2005 USD)	GDP per capita (2005 USD)
Baringo	144	$27,427,881	$151,420,763	$178,848,644	$322
Bomet	99	18,828,734	232,821,568	251,650,302	282
Bungoma	822	157,006,404	329,921,079	486,927,483	354
Busia	243	46,377,729	190,576,644	236,954,373	319
Elgeyo Marakwet	58	11,140,672	97,107,173	108,247,845	293
Embu	970	185,257,500	132,809,566	318,067,066	616
Garissa	737	140,715,702	146,020,607	286,736,309	460
Homa Bay	309	59,084,498	253,101,425	312,185,923	324
Isiolo	168	32,050,749	24,803,077	56,853,826	397
Kajiado	4,628	884,204,321	123,356,381	1,007,560,702	1,466
Kakamega	1,606	306,855,344	431,583,350	738,438,694	445
Kericho	821	156,812,096	111,071,931	267,884,027	454
Kiambu	14,585	2,786,314,569	201,167,607	2,987,482,176	1,785
Kilifi	3,960	756,605,989	252,644,720	1,009,250,708	909
Kirinyaga	1,773	338,751,052	136,291,254	475,042,306	900
Kisii	950	181,490,633	304,012,407	485,503,041	384
Kisumu	2,430	464,139,515	141,360,681	605,500,197	625
Kitui	577	110,200,855	267,525,033	377,725,888	373
Kwale	3,930	750,694,562	163,143,374	913,837,936	1,406
Laikipia	2,080	397,313,865	91,987,784	489,301,649	1,226
Lamu	177	33,868,834	24,919,859	58,788,692	579
Machakos	4,404	841,387,188	161,602,837	1,002,990,025	913
Makueni	677	129,333,676	239,151,073	368,484,750	417
Mandera	86	16,404,162	257,529,013	273,933,175	267
Marsabit	245	46,890,540	69,626,700	116,517,240	400
Meru	2,191	418,562,417	429,436,529	847,998,946	533
Migori	536	102,335,441	185,642,389	287,977,829	314
Mombasa	4,597	878,171,120	0	878,171,120	935
Muranga	3,891	743,300,343	228,927,620	972,227,963	1,090
Nairobi	17,754	3,391,699,448	0	3,391,699,448	1,081
Nakuru	10,466	1,999,522,927	266,145,722	2,265,668,649	1,413
Nandi	402	76,783,764	199,443,468	276,227,232	367
Narok	335	63,916,566	242,889,313	306,805,878	361
Nyamira	193	36,823,500	128,328,644	165,152,144	339
Nyandarua	517	98,761,105	148,888,961	247,650,066	415

Nyeri	4,617	882,097,448	160,595,020	1,042,692,468	1,503
Samburu	52	9,945,126	56,791,752	66,736,878	298
Siaya	294	56,230,908	230,399,192	286,630,100	340
Taita Taveta	793	151,421,576	67,545,780	218,967,356	769
Tana River	605	115,633,298	62,531,831	178,165,129	742
Tharaka Nithi	375	71,734,556	37,260,708	108,995,263	838
Trans Nzoia	452	86,281,073	199,643,621	285,924,694	349
Turkana	241	45,955,610	224,882,867	270,838,477	317
Uasin Gishu	2,129	406,744,065	168,159,468	574,903,533	643
Vihiga	1,020	194,845,744	116,633,620	311,479,363	562
Wajir	368	70,353,845	173,206,520	243,560,366	368
West Pokot	68	13,083,570	144,059,533	157,143,103	307
Kenya	**98,374**	**$18,793,360,520**	**$8,006,968,467**	**$26,800,328,986**	**$694**

Figure 9: County-contribution to overall GDP (%)

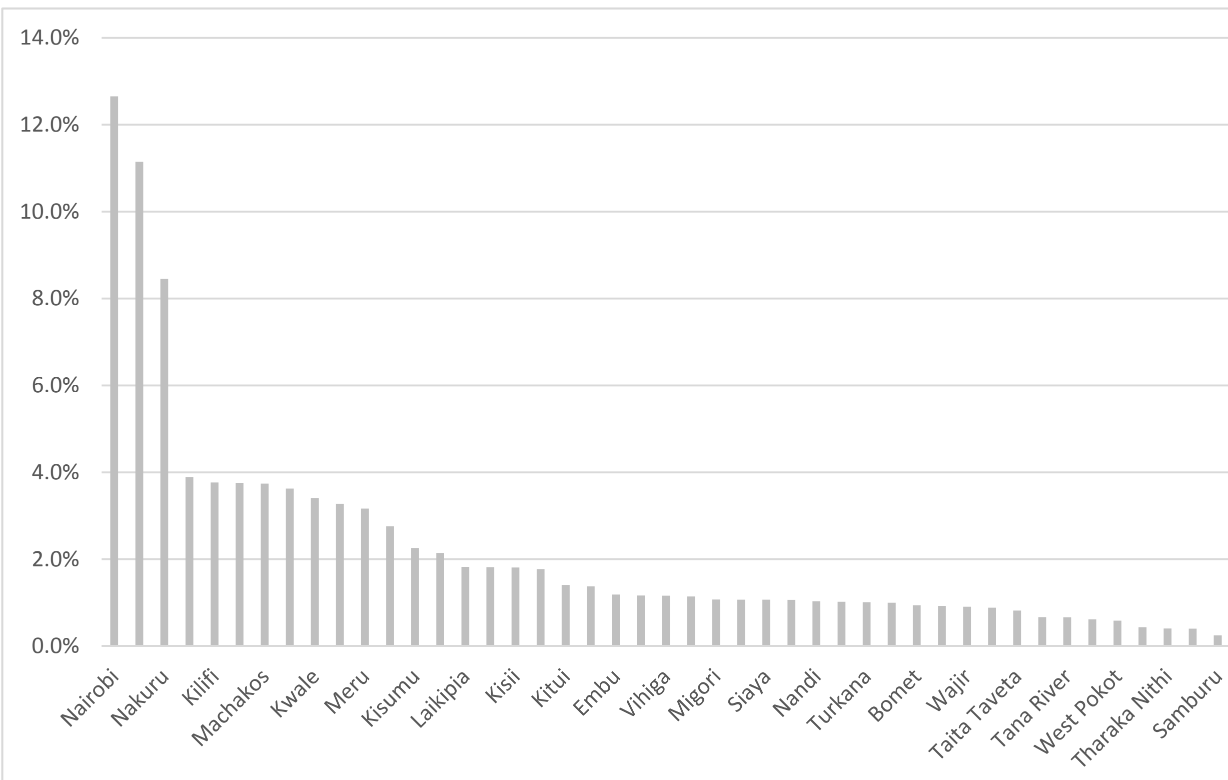
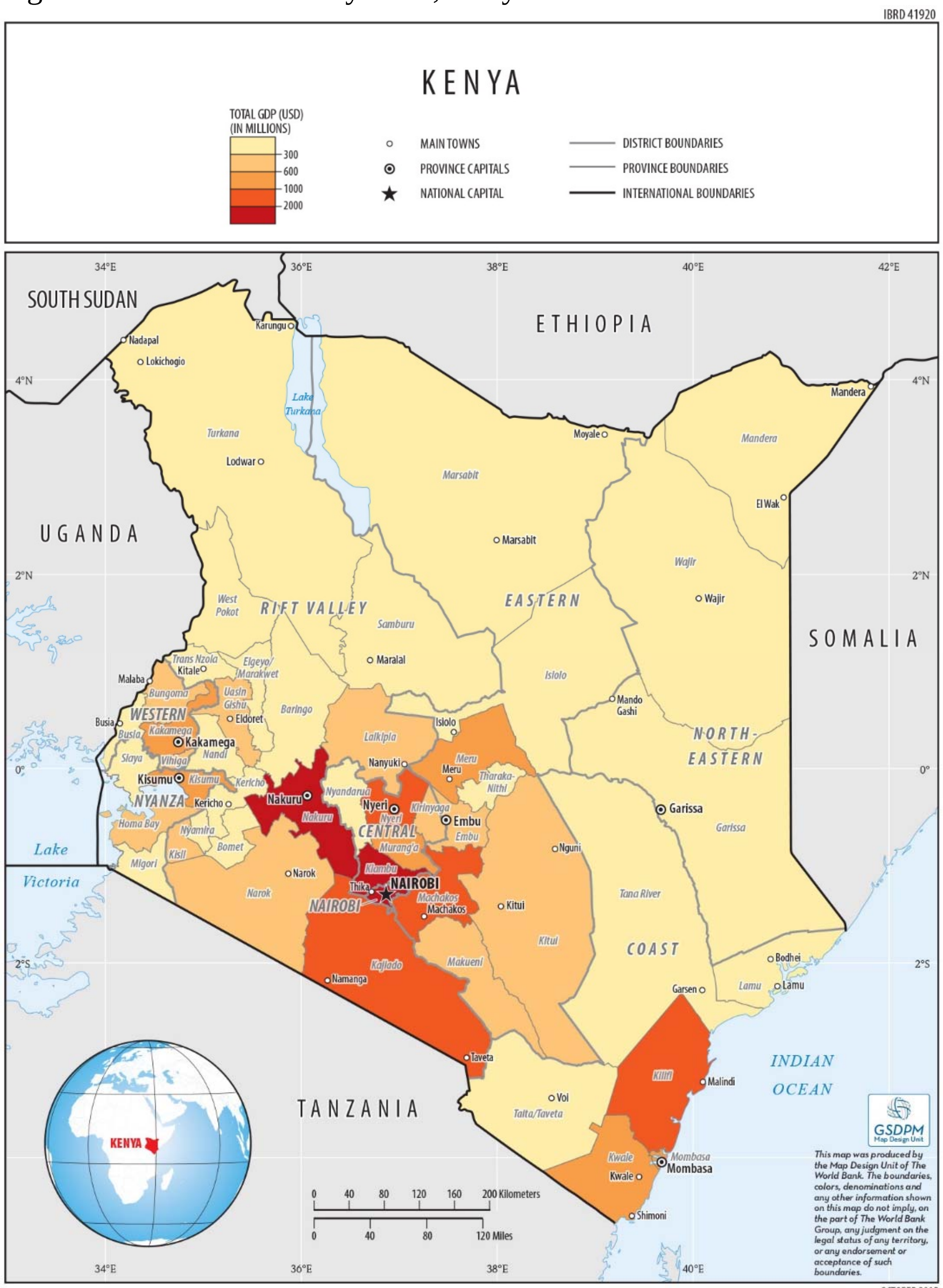


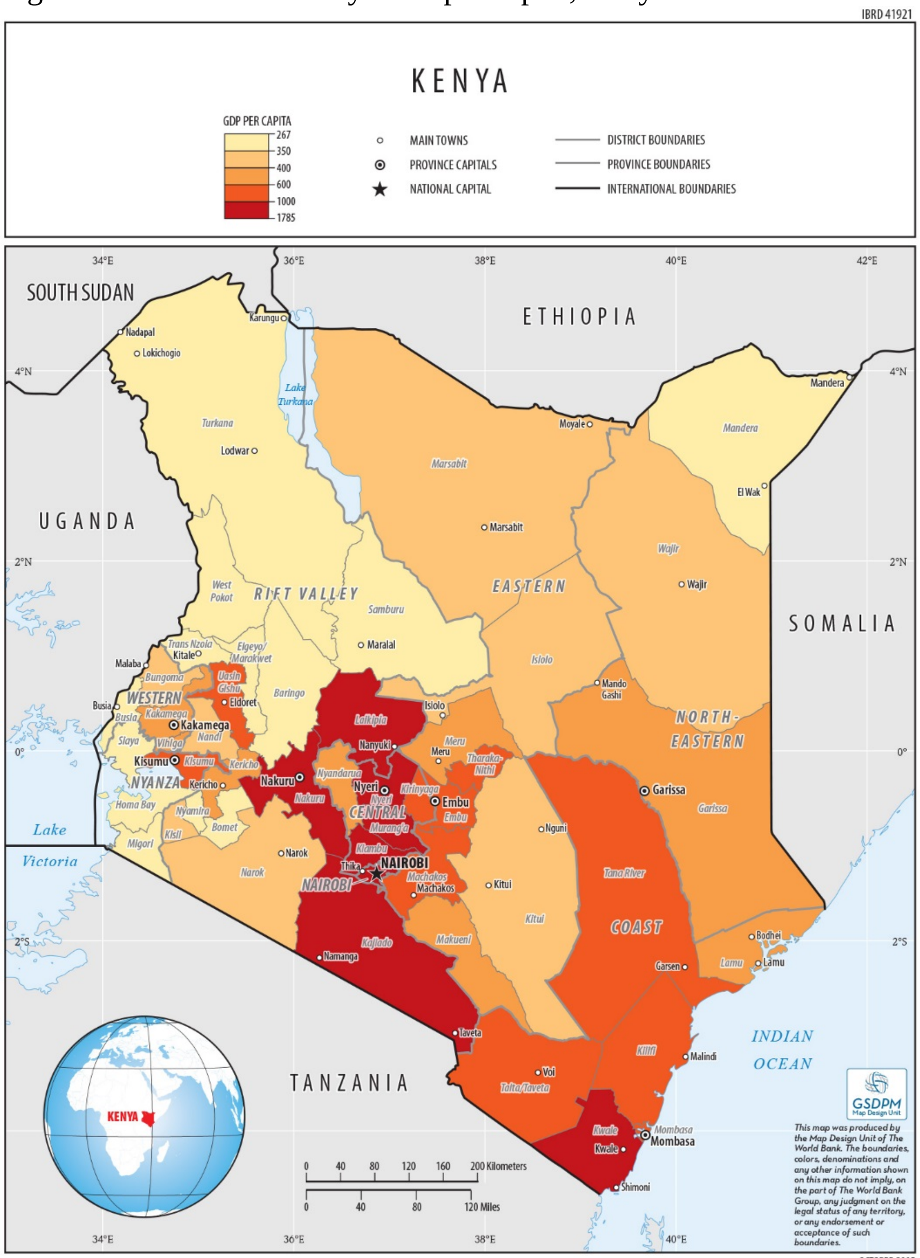
Figure 10: Estimated county GDP, Kenya



Source: WDI (2014) and NGDC (2014). Authors' calculations.

At the other end, Mandera has the lowest GDP per capita ($267), followed by Bomet ($282), Elgeyo Marakwet ($293), Samburu ($298), and West Pokot ($307). Turkana, Busia and Wajir also have low per capita GDP levels. Lamu, while having one of the lowest GDP levels of all counties, ranks higher on GDP per capita (15th spot) thanks to its small population.

Figure 11: Estimated county GDP per capita, Kenya



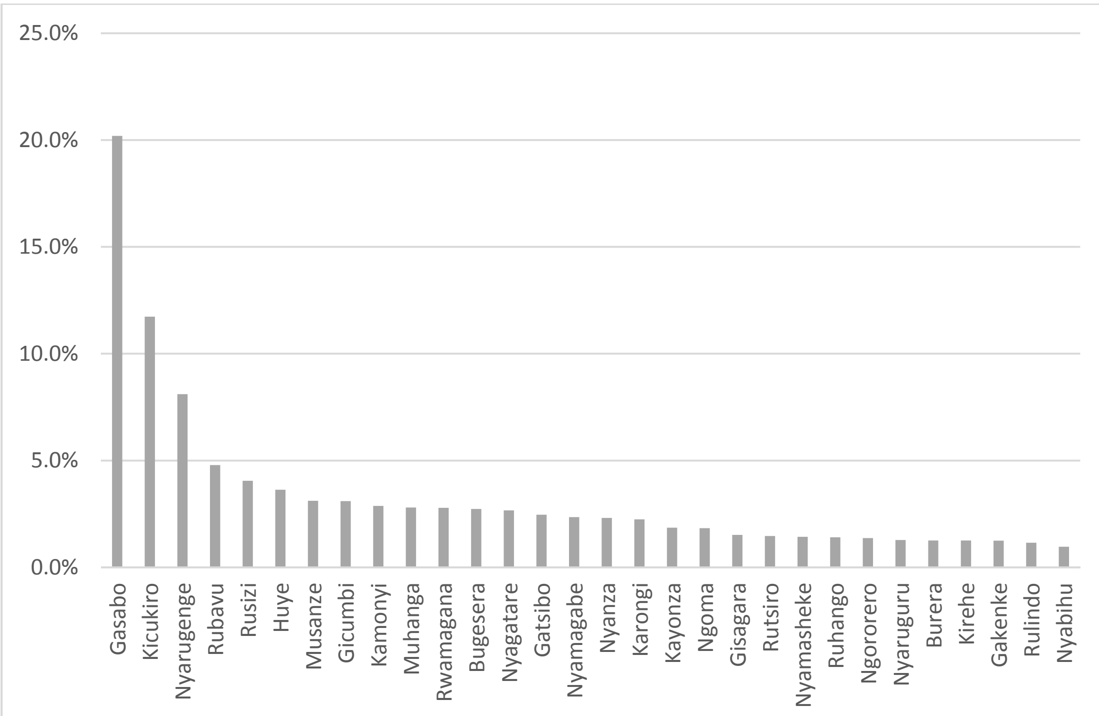
Source: WDI (2014) and NGDC (2014). Authors' calculations.

5.2 Rwanda

Table 6 and Figure 12 show the District-level GDP estimates for Rwanda. Based on specification (1), we estimate total 2013 GDP for Rwanda at \$4.58 billion (2005 USD), only slightly higher than the national-accounts estimate of \$4.57 billion (WDI, 2014). On the district-level, we find that Gasabo district had the highest GDP in 2013 (\$925 million), followed by the two other districts of Kigali (Kicukiro at \$538 million and Nyarugenge at \$371 million). Districts in the secondary urban centers come next: Rubabu (\$219 million), Rusizi (\$186 million), Huye (\$166 million), and

Musanze ($143 million). Districts with the lowest estimated GDP are the largely unlit districts of Nyabihu, Nyaruguru, Burera and Kirehe. Overall, the three districts in Kigali city account for 40 percent of total GDP, despite only accounting for about 10 percent of the population. Adding Rubavu and Rusizi, five districts (out of 30) account for half of overall GDP (Figure 9).

Figure 12: District-level contribution to overall GDP



When we control for population by looking at GDP per capita, there are only a few changes (Figure 8). The districts in Kigali city remain the wealthiest (in the same order), while Rubavu remains the wealthiest district outside Kigali. Huye comes fifth ($507 per capita), followed by Rusizi ($463) and Rwamagana (408).

Table 6: Estimates of District-Level GDP in Rwanda, 2013 (in constant 2005 USD).

Districts	Sum of lights (2013)	GDP (services and industry) USD	GDP (agriculture) USD	Total GDP (USD)	GDP per capita
Bugesera	313	67,295,950	57,925,612	125,221,562	346
Burera	0	0	57,447,257	57,447,257	171
Gakenke	0	0	57,188,170	57,188,170	169
Gasabo	4,173	896,487,039	28,550,005	925,037,044	1,747
Gatsibo	195	41,863,156	71,136,966	113,000,122	261
Gicumbi	368	79,139,205	62,782,886	141,922,091	359
Gisagara	67	14,441,452	55,207,284	69,648,736	216

Huye	551	118,432,522	47,927,632	166,360,154	507
Kamonyi	369	79,304,916	52,420,098	131,725,014	387
Karongi	230	49,324,244	53,739,182	103,063,425	311
Kayonza	145	31,236,863	53,929,932	85,166,795	247
Kicukiro	2,471	530,886,041	6,715,920	537,601,961	1,688
Kirehe	0	0	57,431,259	57,431,259	169
Muhanga	380	81,740,210	46,693,578	128,433,788	402
Musanze	448	96,329,234	46,285,298	142,614,533	387
Ngoma	130	27,941,618	55,937,075	83,878,693	249
Ngororero	31	6,748,616	55,898,125	62,646,741	188
Nyabihu	0	0	44,178,173	44,178,173	150
Nyagatare	230	49,521,538	72,748,696	122,270,235	262
Nyamagabe	246	52,749,857	55,042,094	107,791,951	316
Nyamasheke	0	0	65,322,461	65,322,461	171
Nyanza	251	53,943,836	51,869,929	105,813,766	327
Nyarugenge	1,671	359,038,297	12,265,948	371,304,245	1,305
Nyaruguru	39	8,307,465	50,150,217	58,457,682	199
Rubavu	814	174,951,644	44,245,292	219,196,936	543
Ruhango	61	13,198,341	51,091,625	64,289,966	201
Rulindo	20	4,224,944	48,522,489	52,747,433	183
Rusizi	590	126,816,350	58,703,221	185,519,570	463
Rutsiro	55	11,875,809	55,229,019	67,104,829	207
Rwamagana	363	77,958,370	49,818,099	127,776,468	408
Rwanda	**14,214**	3,053,757,518	1,526,403,540	4,580,161,058	436

Source: WDI (2014) and NGDC (2014). Authors' calculations.

As evident from the title of this paper, we also tried to estimate poverty levels and changes based on nightlights data. The estimated associations were however not robust, and more time and effort would need to be invested in examining this relationship in a more detailed fashion. This will be pursued in further work.

6. Conclusions

In this paper, we have adapted the methodology of Henderson, Storeygard and Weill (2012) to examine the association between night lights and GDP for a sample of 46 countries in Sub Saharan Africa. Overall, we find a fairly strong correlation between the intensity of night lights as measured by satellites and country-level GDP, with even small and temporary economic downturns being reflected in the intensity of lighting. As expected, we find that the association between lights and economic activity is stronger in countries where agriculture is a smaller part of GDP (where more economic activity is lit). We apply the regression results to estimate subnational GDP levels and growth in Kenya and Rwanda. To our knowledge, this is the first time such an exercise to estimate county-level GDP levels and growth for Kenya and Rwanda has been attempted.

Our first-approximation results yield some interesting findings. In the case of Kenya, our results affirm that Nairobi county contributes the maximum to national GDP. However, at only 13%, this contribution is significantly lower (compared with 60%) than commonly thought. Controlling for population, Kiambu is the best-off county, with a per capita GDP of $1,785 (2005 USD), followed by Nyeri ($1,503), Kajiado (1,466), Nakuru ($1,413), and Kwale ($1,406). Due to its large population, Nairobi does not make it to the top five with an estimated per capita GDP of $1,081 (ranked 8th among the 47 counties, one spot in front of Mombasa). In the case of Rwanda, the three districts of Kigali account for 40 percent of overall GDP, and, adding the secondary cities of Rubavu and Rusizi, only five districts account for half of national GDP.

While the results from the analysis in this paper show promise, there is ample room to improve on the methodology. Several issues in particular stand out: first, the accuracy of the subnational estimates is likely to be affected by over-glow, meaning that lights (and economic activity) could be attributed to the wrong subnational unit. This is particularly a worry in heavily lit areas in urban agglomerations. Second, given the importance of agriculture in the economy of many countries in our sample, the estimates could be improved by including proxies for agricultural performance, such as rainfall or vegetation cover. Also, subnational variation in rainfall or vegetation cover could be used to allocate agricultural GDP across subnational units, rather than the units' share of total rural population. Future work will address this (for an application, see Rogers, Emwanu and Robinson, 2006). To get a more composite picture of subnational economic activity, it is also important to estimate subnational GDP through the standard approaches (production, expenditure, income) that have their strengths and limitations. This is however outside the scope of this paper and a topic that we propose for future investigation.

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