Using Nighttime Luminosity as a Proxy for Economic Growth in Africa: Is It a Bright Idea?

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In this paper, we question whether night light luminosity data can be used as an alternative measure of GDP in 49 African countries. For this to be proven true, evidence of significant relationships between night light data and GDP time series variables needs to be confirmed through empirical analysis. In differing from previous studies, we employ pooled mean group (PMG) cross sectional cointegration estimators and wavelet coherence tools to examine the cointegration relationships and time-frequency synchronizations between GDP and DMSP-OLS night light intensity for annual data collected between 1992 and 2012. All in all, we find little evidence of significant relationships between nighttime data and GDP for individual African countries and therefore caution policymakers in strictly using DMSP-OLS data to create synthetic measures of economic growth. Possible avenues for future research are further recommended at the end of the study.

Key Words: DMSP-OLS night light, economic growth, complex wavelet analysis, Morlet wavelets, Africa
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Introduction

Over the last couple of decades, there has been much debate on the reliability of gross domestic product (GDP) as a standard measure of economic activity (Deaton 2005; Johnson et al. 2013; Dynan and Sheiner 2018) and economists have contemplated adopting alternative, 'out-of-this-world' remote sensing measures of human activity in the form of night light intensity data obtained from satellite sensors in outer space. Following Croft's (1978) demonstration on how a series of images obtained from the US Air Force Meteorological Satellite sensors can capture and distinguish between city-level activity (city lights) in advanced European countries, gas flares in the Middle East and Northern Africa (MENA) region, a fleet of well-lit fishing boats along the coast of Japan, agriculture fires in Mexico, and natural fires along the Australian coast as well as the pattern of population distribution across the US states, many researchers have used similar night light intensity data to track economic activity at the national level (Elvidge et al. 1997; Doll, Muller, and Elvidge 2000; Sutton and Costanza 2002; Henderson, Storeygard, and Weil 2011; 2012; Chen and Nordhaus 2011, Nordhaus and Chen 2012; 2015; Pinkovskiy and Sala-i-Martin 2016; Guerrero and Mendoza 2019; Galimberti 2020), state level (Doll, Muller, and Morley 2006; Ghosh et al. 2010; Hu and Yao 2019; Chanda and Kabiraj 2020), regional level (Sutton¸ Elvidge, and Ghosh 2007; Ghosh et al. 2009; Omar and Ismal 2019), provincial level (Zhao, Currit, and Samson 2011; Propastin and Kappas 2012; Nonso 2015; Coetzee and Kleyhans 2021a; 2021b), district level (Bhandari and Roychowdhury 2011; Forbes 2011; 2013; Wang et al. 2019), and city-level (Ma et al. 2014; Roberts 2021; Perez-Sindin, Chen, and Prishchepov 2021) as well as across different economic sectors such as primary, secondary and tertiary levels (Keola, Anderson, and Hall 2015; Chen et al. 2021).

In the context of African countries, the use of night light intensity as a proxy for economic growth is of more appeal considering that the continent suffers from problems of reliable economic data mainly due to low levels of resources available to national statistics offices (Devarajan 2013; Jerven 2013). Data derived from satellite imagery holds several advantages over traditional survey-based data in the sense that it is easily and widely available, relatively cheap to obtain, and is not subjected to any statistical inference in the way that it is created (Bluhm and Krause 2018). Notably, there already exists a handful of papers which have made use of night light data as proxies for African economic statistics such as urbanization (Abay and Amare 2018), municipal and electoral district level activity in South Africa during the 2010 World Cup (Pfeifer, Wahl, and Marczak 2016), human development in Africa (Bruederie and Hodler 2018), regional inequality trends in Africa (Mveyange 2015), district-level economic growth (Coetzee and Kleynhans 2021a; 2021b), and detection of rural electrification (Min et al. 2013).

Despite the widespread use of nighttime lights as a proxy for economic activity, it is interesting to note that such proxies are built on the theoretical assumption of some form of correlation existing between luminosity and measured economic growth (Chen and Nordhaus 2011; Henderson, Storeygard, and Weil 2011; 2012; Pinkovskiy and Sala-i-Martin 2016). Only if a relationship exists between the two variables at the national level, can night light data be used as a predictor of economic growth at various sub-national levels where nighttime data is available and there is insufficient GDP data. Whilst many previous studies have relied on cross-section estimates, time series and/or panel data modelling to validate the relationship between night lights obtained from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) night lights and GDP (see the second section for detailed discussion of the literature), our study challenges the reliability of these previous results based on three criticisms. Firstly, the cross-section estimates used in most previous literature failed to account for heterogeneity effects amongst a host of countries with different developmental characteristics. Secondly, with the sole exception of Coetzee and Kleyhans (2021a; 2021b), previous studies have ignored possible cointegration effects, hence failing to distinguish between short-run and long-run co-movements along the steady state. Thirdly, previous studies do not adequately account for possible time-varying and asymmetric effects of night light activity on economic growth. Whilst some studies attempt to test for nonlinear effects by including a 'squared interactive term' in the estimated regression, they all fail to observe a significant coefficient on the interactive term (Zhao, Currit, and Samson 2011; Henderson, Storeygard, and Weil 2012; Hu and Yao 2019; Chanda and Kabiraj 2020; Otchia and Asongu 2020).

To deal with the empirical shortcomings identified from previous studies, we re-examine the relationship between DMSP-OLS night lights and GDP for 49 African countries between 1992 and 2018 using the pooled mean group (PMG) cointegration estimators of Pesaran, Shin, and Smith (1999) as well as continuous complex wavelet coherence tools discussed in Aguiar-Conraria and Soares (2014). On the one hand, the PMG estimators are used to capture the panel cointegration effects between night lights and GDP whilst providing short-run cross-sectional estimates for individual countries. On the other hand, we make use of complex wavelet coherence techniques which allows us to decompose the time series along a time-frequency space and thereafter yield localized time-frequency information on the series. Since wavelets can localize a time series in both time and frequency via dilation and translation operators, they ultimately allow us to capture various forms of asymmetries existing in the time series which reflect structural changes in the economy and the changing lengths of business cycles. This differs from the PMG estimators and other traditional estimators used in the literature, which are strictly localized in time and therefore provide little to no information on possible time-varying or frequency-varying relationships between the variables.

The main contribution of our study is that it is the first to examine the relationship between night light and GDP for individual African countries, whereas previous African-related studies have relied on panel-based estimations (Nonso 2015; Otchia and Asongu 2020). Consequently, by taking a country-specific approach using more advanced empirical techniques, our study distinguishes between those African countries which display significant correlations between night light intensity and GDP and those which do not. This, in turn, has important policy implications as it allows us to determine which African economies can use regression analysis to create synthetic time series measures of GDP data at the subnational level based on luminosity data.

The rest of the study is organized as follows. The following section presents the literature review of the study. The third section outlines the empirical methods used in the study. The fourth section presents the data and empirical analysis. The fifth section concludes the study in the form of policy recommendations and avenues for possible future research.

Literature Review

Whilst acknowledging the extensive empirical applications of high spatial resolution satellite imagery following the release of the DMSP-OLS archive in mid-1992 (see Donaldson and Storeygard 2016; Gibson, Olivia, and Boe-Gibson 2020; and Levin et al. 2020 for reviews of the different academic uses of nighttime light data), our study is specifically related to literature which has examined the empirical relationship between luminosity and GDP and has used the predicted values from the regressions to either (i) map out GDP-night light activity across different countries, or (ii) provide estimates of GDP in regions where there exists night light data but insufficient GDP statistics.

In reviewing the literature, we focus on the empirical estimates obtained in previous studies which have used a regression of the form $\text{GDP} = a + \beta\text{NTL} + e_t$, (where NTL is nighttime intensity) to validate the existence of a significant GDP night light relationship for various samples. To facilitate a discussion of the previous studies, we find it most convenient to segregate the literature into two broad strands of empirical works, the first of which provides cross-sectional estimates of the baseline regression, and the second of which uses time-series and/or panel methods for regression analysis. The coefficient estimates (β) and the coefficient of determination (R^2) of the estimated regressions, which are the two most common measures of the strength of a linear relationship obtained in previous studies are summarized (together with other details of the literature) in tables 1 and 2, respectively.

Table 1 summarizes the empirical findings from the strand of studies which have examined the cross-sectional relationship between luminosity and GDP across a single time period. Notably, these cross-sectional studies have either used country-level data to produce a singular estimate for all countries (Elvidge et al. 1997; Doll, Muller, and Elvidge 2000; Sutton and Costanza 2002; Zhao, Currit, and Samson 2011; Nonso 2015), or have used regional or sector-level data of singular countries to produce national level estimates (Doll, Muller, and Morley 2006; Sutton, Elvidge, and Ghosh 2007; Ghosh et al. 2009; Bhandari and Roychowdhury 2011; Ma et al. 2014) and as can be observed, most reviewed studies produce positive and statistically significant β coefficient estimates with relatively high R^2 values. An exception is observed for the study conducted by Nonso (2015) for 48 African countries which reports a low R^2 value of 0.418.

Table 2 summarizes the empirical findings from the strand of studies which either use time series and/or panel analysis to examine the GDP luminosity relationship and produce more variability in empirical findings. Chen and Nordhaus (2011), Henderson, Storeygard, and Weil (2011; 2012) and Pinkovskiy and Sala-i-Martin (2016) were amongst the first to use panel analysis over a large sample of countries to validate the existence of a GDP night light relationship but do very little to account for heterogeneity effects. Nordhaus and Chen (2012; 2015) segregate a large sample of countries according to the 'grade' of their national statistics and apply both time series and panel estimators to find significant relationships (i.e. higher β and R^2 values) for countries with the lowest data grade qualities. For a sample of 24 countries, Keola, Anderson, and Hall (2015) segregate the data according to the countries' share of GDP in the agriculture sector and apply panel estimation techniques to find insignificant β estimates for countries with higher shares of GDP in agriculture. Bickenbach et al. (2016) use panel regressions to estimate both national and regional relationships between luminosity and GDP for Western European countries and the US and find that the β coefficient at the regional level is either negative or insignificant. Omar and Ismal (2019) estimate

TABLE 1 Summary of Cross-Sectional Literature

Authors	Sample	Period	Coefficient estimate and R^2
Elvidge et al. (1997)	19 non-African emerging countries and the US	1994	$\beta = 1.159$ ($R^2 = 0.97$)
Doll, Muller, and Elvidge (2000)	46 countries	October 1994 and March 1995	$\beta = 0.9735$ ($R^2 = 0.85$)
Sutton and Costanza (2002)	122 countries	1995–1996	$\beta = 1.05$ ($R^2 = 0.86$)
Doll, Muller, and Morley (2006)	Subnational level for 11 European countries and US	1996–1997	Coefficient range from 0.0499 (USA) to 0.2103 (Germany); R^2 from 0.75 (France) to 0.99 (Portugal)
Sutton, Elvidge, and Ghosh (2007)	Subnational level for China, India, Turkey, US	1992–1993 and 2000	China: $R^2 = 0.94(0.96)$ India: $R^2 = 0.70(0.84)$ Turkey: $R^2 = 0.58(0.95)$ US: $R^2 = 0.70(0.72)$
Ghosh et al. (2009)	Subnational level for China, India, Mexico, US	2006	China: $\beta = 10.16$ ($R^2 = 0.97$) India: $\beta = 2.16$ ($R^2 = 0.99$) Mexico: $\beta = 1.10$ ($R^2 = 0.99$) US: $\beta = 0.57$ ($R^2 = 0.99$)
Bhandari and Roychowdhury (2011)	India, district level (35 states, 593 districts)	2008	Multivariate GDP: $\beta = 0.36$ ($R^2 = 0.79$) GDP.pri: $\beta = 0.30$ ($R^2 = 0.73$) GDP.sec: $\beta = 0.50$ ($R^2 = 0.73$) GDP.ter: $\beta = 0.30$ ($R^2 = 0.87$)
Zhao, Currit, and Samson (2011)	For subset of 31 Chinese provinces	1996 and 2000	Estimate OLS regression with squared terms for nonlinearity GDP.1996: $\beta = 0.6029$ ($R^2 = 0.66$) GDP.2000: $\beta = 0.7507$ ($R^2 = 0.69$)
Forbes (2013)	US states/ metropolitan levels	2006 and 2010	MSA: $\beta = 0.244$ to 0.691 (R^2 0.976 to 0.845) State: $\beta = 0.482$ to 0.696 (R^2 0.976 to 0.878)

a panel regression of night light intensity and gross governorate product (GGP) for 27 Egyptian governorates and obtain positive β coefficient estimates and high R^2 at both the national and subnational level. Guerrero and Mendoza (2019) estimate country-specific time series regressions for

TABLE 2 Summary of Time-Series Literature

Authors	Sample	Period	Coefficient estimate and R^2
Ma et al. (2014)	Chinese cities	2012	GDP ($R^2 = 0.91$)
Nonso (2015)	48 African count.	1999 and 2012	$\beta = 1.384$ ($R^2 = 0.418$)
Chen and Nordhaus (2011)	170 countries	1992–2008	Time series and cross-sectional estimates/ Correlation coefficient between 0.797 and 0.842
Henderson, Storeygard, and Weil (2011)	118 countries	1992–2006	FE: $\beta = 0.308$ ($R^2 = 0.78$) Country time trend: $\beta = 0.270$ ($R^2 = 0.903$) Long difference: $\beta = 0.329$ ($R^2 = 0.301$)
Henderson, Storeygard, and Weil (2012)	188 countries	1992–2008	$\beta = 0.22$ ($R^2 = 0.769$) Squared negative and insignificant (−0.00058)
Nordhaus and Chen (2012)	170 countries (5 quality grade levels from A to E)	1992–2008	Cross sectional A: $\beta = 0.777$ B: $\beta = 0.742$ C: $\beta = 0.990$ D: $\beta = 0.952$ E: $\beta = 1.318$ Time series A: $\beta = 0.161$ B: $\beta = 0.251$ C: $\beta = 0.424$ D: $\beta = 0.882$ E: $\beta = 0.011$
Propastin and Kappas (2012)	Kazakhstan/17 provinces	1994–1999 and 2004–2009	Province: $\beta = 0.6903$ ($R^2 = 0.76$) Total: $\beta = 0.0048$ ($R^2 = 0.94$)

Continued on the next page

Mexico, China and Chile, and also find positive β estimates and high R^2 values.

It is also interesting to note that there exist some literatures which have put forward arguments in favour of a possible nonlinear relationship between GDP and night lights. For instance, Hu and Yao (2019) argue that the relationship between nighttime lights and true GDP per capita is most likely nonlinear as it varies with geographic location. Chen et al. (2021) argue for a nonlinear relationship on the basis of diverse indus-

TABLE 2 *Continued from the previous page*

Authors	Sample	Period	Coefficient estimate and R^2
Nordhaus and Chen (2015)	167 countries (5 quality grade levels from A to E)	1992–2010	Cross sectional A: $\beta = 0.779$ B: $\beta = 0.773$ C: $\beta = 0.980$ D: $\beta = 0.953$ E: $\beta = 1.318$ All: $\beta = 0.953$ Time series A: $\beta = 0.424$ B: $\beta = -0.486$ C: $\beta = 0.014$ D: $\beta = 1.253$ E: $\beta = 0.001$ All: $\beta = 0.322$
Keola, Anderson, and Hall (2015)	24 African, emerging and industrialized countries	1992–2009	GDP by agriculture share: >10%: $\beta = 0.67453$ 10–20%: $\beta = 0.39278$ 20–30%: $\beta = -0.408595$ 30–40%: $\beta = -0.50387$ 40–50%: $\beta = 0.0235$ (insign.) <50%: $\beta = 0.03823$ (insign.) Estimate for agriculture at national level: $\beta = 0.028$ (insign.)
Bickenbach et al. (2016)	Brazil, India, Western Europe and US	1995–2010	India: $\beta = 0.10$ ($R^2 = 0.060$) Brazil: $\beta = 0.148$ ($R^2 = 0.045$) US: $\beta = 0.164$ ($R^2 = 0.048$) Western Europe: $\beta = 0.113$ ($R^2 = 0.024$) Coefficient on NTL at regional level is either -ve or insignificant

Continued on the next page

trial structures, socioeconomic patterns, and development levels which exist in studies which use a large number of countries. Galimberti (2020) attributes nonlinear effects to differences in the sectoral composition of a country's GDP, where some industries may generate more lights than others and also to satellite sensor noise which causes production activities to be reflected by nighttime lights in a nonmonotonic manner. Notably, there are a few empirical studies which have tested for a possible non-

TABLE 2 *Continued from the previous page*

Authors	Sample	Period	Coefficient estimate and R^2
Pinkovskiy and Sala-i-Martin (2016)	123 countries	1992–2010	National accounts: $\beta = 1.160$ ($R^2 = 0.72$) Surveyed income: $\beta = 1.286$ ($R^2 = 0.63$)
Omar and Ismal (2019)	Egypt, 27 governorates	2008–2013	$\beta = 0.69$ ($R^2 = 0.80$)
Guerrero and Mendoza (2019)	Mexico, China, Chile	1992–2008	Mexico: $\beta = 0.808$ China: $\beta = 1.204$ Chile: $\beta = 1.139$
Hu and Yao (2019)	162 countries/BRICS countries and 4 low-income African countries (Congo, Ethiopia, Kenya, Sierra Leone)	1992–2013	NTL = a + GDP $\beta = 0.5351$ to 0.662 ($R^2 = 0.0109$ to 0.439) Squared terms are insignificant
Chanda and Kabiraj (2020)	520 Indian districts: also distinct between rural and urban places	1992–2013	State level regression: $\beta = 0.591$ ($R^2 = 0.396$) Squared term insignificant
Otchia and Asongu (2020)	46 African countries	1992–2013	Total: $\beta = 0.259$ ($R^2 = 0.837$) Agric.: $\beta = 0.236$ ($R^2 = 0.576$) Manu.: $\beta = 0.257$ ($R^2 = 0.536$) Ind.: $\beta = 0.513$ ($R^2 = 0.683$) Service: $\beta = 0.268$ ($R^2 = 0.780$) (Insignificant squared terms)

linear relationship between GDP and night lights by adding a quadratic term to the baseline regression. However, these studies fail to find a significant estimate on the squared term coefficient at both the national (Zhao, Currit, and Samson 2011; Henderson, Storeygard, and Weil 2012; Hu and Yao 2019; Chanda and Kabiraj 2020) and sectoral level (Otchia and Asongu 2020).

Our study draws and improves on three aspects of the current literature. Firstly, we expand on the literature for African economies of which the works of Nonso (2015) and Otchia and Asongu (2020) are currently the only studies available in the literature which provide regression estimates between GDP and night light intensity. Secondly, we differ from

Nonso (2015) and Otchia and Asongu (2020) by taking a country-specific, time series approach to estimating the night light GDP relationship as in the studies of Guerrero and Mendoza (2019) for Mexico, China and Chile. Thirdly, since previous studies have investigated possible cointegration effects between night light intensity and GDP, our study employs PMG estimators to investigate cross-sectional relationships of the individual African countries across the steady-state equilibrium. Lastly, in differing from previous studies which use quadratic terms as a measure turning points in the data as a means of capturing nonlinearity, this study employs wavelet coherence which examines the asymmetric co-movement between the variables across five dimensions, namely (i) strength variation, (ii) time variation, (iii) frequency variation, (iv) direction of relationship (negative or positive), and (v) phase dynamics (causality between the time series). The PMG estimators and wavelet coherence tools used in this paper are outlined in the following section.

Methods

PMG ESTIMATORS

The pooled mean group (PMG) estimator of Pesaran, Shin, and Smith (1999) can be obtained from the following panel autoregressive distributive lag (P-ARDL $(p, q, q, \ldots, q)$ model:

$$\mathrm{GDP}_{it} = \sum_{j=1}^{p} \lambda_{ij}\mathrm{GDP}_{i,t-j} + \sum_{j=0}^{q} \delta_{ij}\mathrm{NTL}_{i,t-j} + \alpha_i + \varepsilon_{it}, \tag{1}$$

where $t = 1, 2, \ldots, T$, $i = 1, 2, \ldots, N$, α_i is the fixed effect, and λ_{ij} and δ_{ij} are vectors of parameters. The error correction representation of equation (1) is:

$$\begin{aligned}\Delta\mathrm{GDP} = \phi_i\mathrm{GDP}_{i,t-1} + NTL_{it}\beta_i + \sum_{j=1}^{p-1} \lambda^{*}_{ij}\Delta\mathrm{GDP}_{i,t-1} \\ + \sum_{j=0}^{q-1} \Delta\mathrm{NTL}_{i,t-j}\delta^{*}_{ij} + \mu_i + \varepsilon_{it},\end{aligned} \tag{2}$$

where ε_{it} are serially not correlated across i and t, have zero means, variance $\sigma_i^2 > 0$, and finite fourth-order moment conditions, and:

$$\phi_i = \frac{-1}{1 - \sum_{j=1}^{p} \lambda_{ij}} \quad \text{and} \quad \beta_i = \sum_{j=0}^{q} \delta_{ij}. \tag{3}$$

The long-run relationship can compactly be denoted as:

$$\text{GDP}_{it} = \theta_i \text{NTL}_{it} + \eta_{it}, \tag{4}$$

where: $\theta_i = -\frac{\beta_i'}{\phi_i}$ are the long run-run coefficients and η_{it} is a stationary process. The long-run coefficients defined by θ_i are constrained to be the same for all cross-sectional units and can be expressed as:

$$\Delta\text{GDP}_i = \phi_i \xi_i(\theta) + W_i k_i + \varepsilon_i, \qquad i = 1, 2, \ldots, N \tag{5}$$

with

$$W_i = \Delta\text{GDP}_{i,-1}, \ldots, \Delta\text{GDP}_{i,-P+1}, \Delta\text{NTL}_i, \text{NTL}\Delta_{i,-1}, \ldots, \\ \Delta\text{XNTL}_{i,-q+1,\iota} \tag{6}$$

$$k_i = (\lambda_{i1}^*, \ldots, \lambda_{i,p-i}^*, \delta_{i0}^{*\prime}, \delta_{i1}^{*\prime}, \ldots, \delta_{i,-q-1}^{*\prime}, \mu_i)' \tag{7}$$

and the error correction term is computed as:

$$\xi_i(qtheta) = \text{GDP}_{i,-1} - \text{NTL}_i\theta \qquad i = 1, 2, \ldots N. \tag{8}$$

And this measures the speed of 'correction' back to steady-state equilibrium following a shock to the system of time series variables.

WAVELET COHERENCE ANALYSIS

Wavelets are small waves that stretch and compress in a limited time-period and are used to decompose a signal or time series across a time-frequency plane; these transforms can either be discrete (returns data vector of the same length as the input signal) or continuous (returns an output vector which is one dimension higher than the input). In our study, we focus on continuous wavelet transforms (CWT) of the GDP and NTL data:

$$W_{\text{GDP}}(s,\tau) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{s}}\psi^*(\frac{t-\tau}{s})dt \tag{9}$$

$$W_{\text{NTL}}(s,\tau) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{s}}\psi^*(\frac{t-\tau}{s})dt, \tag{10}$$

where τ and s are time and scale parameters responsible for dilation and translation of the wavelet in time frequency space. To explore the instantaneous phase information in the time-scale plane, a complex mother wavelet is required; in this study we use complex Morlet wavelets which are complex sinusoids modulated by a Gaussian envelope:

$$\psi(t) = \pi^{-\frac{1}{4}} \exp(i\omega_c t) \exp(-\frac{1}{2}t^2), \tag{11}$$

where $\omega_c = 2\pi f_c$ is the central frequency of the wavelet and determines the number of oscillations of the complex sinusoid inside the Gaussian. To ensure equation (11) is admissible as a wavelet, with a zero-mean function, we set $\omega_c = 6$. The term $\pi^{-\frac{1}{4}}$ ensures the wavelet has unit energy. Since the wavelet function is complex, the wavelet transform is also complex and can be divided into a real and imaginary part. The wavelet power spectrum (WPS) for a discrete series measures the variance of the GDP and NTL series across a time-scale dimension, i.e.

$$\text{WPS}_{\text{GDP}}(\tau, s) = |W_{\text{GDP}}(\tau, s)|^2 \tag{12}$$

$$\text{WPS}_{\text{NTL}}(\tau, s) = |W_{\text{NTL}}(\tau, s)|^2 \tag{13}$$

and using (12) and (13) we can compute the Cross-Wavelet Power Spectrum (CWPS) between GDP and NTL which is analogous to the covariance between the variables in time-frequency domain.

$$(\text{CWPS})_{\text{GDP,NTL}} = W_{\text{GDP,NTL}} = W_{\text{GDP,NTL}}. \tag{14}$$

The wavelet coherency is referred to as the ratio of the cross spectrum to the product of each series spectrum and can be thought of as the local correlation between the pair of time series in time-frequency space, i.e.

$$R_n(s) = \frac{|S(W_{\text{GDP,NTL}})|}{[(S|W_{\text{NTL}}|^2)(S|W^2_{\text{GDP}})]^{\frac{1}{2}}}, \tag{15}$$

where $0 \leq R_n(s) \leq 1$ and S is a smoothing operator in both time and scale. To further distinguish between negative and positive correlation between a pair of time series as well as identifying lead-lag causal relationships between the variables, we explore phase difference dynamics through a complex number which is parametrized in radians:

$$\phi_{\text{NTL,GDP}} = \tan^{-1}(\frac{\mathcal{I}\{W_{\text{NTL}}\}}{\mathcal{R}\{W_{\text{NTL}}\}})), \tag{16}$$

where $\phi_{\text{NTL,GDP}}$ is bound between π and $-\pi$ which encompasses all possible lead-lag synchronizations between the time series in a time-frequency plane.

Data and Empirical Findings

DATA DESCRIPTION

This study uses two sets of time series variables, GDP and night light intensity, collected for 39 Sub-Saharan African (SSA) countries, on annual frequency between 1992 and 2012. Firstly, GDP data is sourced from the World Bank Development (WBD) indicators. Secondly, the DMSP-OLS night light time series dataset is retrieved from the US Air Force sub-division Earth Observation Group's (EOG-NOAA) online website (https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html). The DMSP-OLS oscillating scanning devices observe all locations around the planet with the intention to capture some indoor and outdoor utility of lights using high resolution technology. Under the DMSP-OLS program there are approximately 5 sensors namely, F10 (for years 1992–1994), F12 (for years 1994–1999), F14 (for years 1997 to 2000), F15 (for years 2000 to 2008), F16 (for years 2004 to 2008) and F18 (for years 2009–2013). The images are 30 arc second grids which span –1800 to 1800 longitude and –650 to 750 latitude. The raw dataset values range between 0 (no light activity) and 63 (strongest light intensity activity), with the exception of the value 255 representing areas with zero cloud-free observations and the ephemeral events such as fires and background noise have been eliminated and replaced with 0. We focus on the mean lights and compute annual growth rates at the second administrative regions (ADM2) level for our sample data.

Table 3 presents the descriptive statistics, unit root properties and correlation indices for GDP and nighttime lights (NTL), whilst figure 1 presents time series plots of the variables for the individual African countries. Note that both the panel correlation coefficient reported in table 3 and visual appreciation of the time series data in figure 1 present preliminary evidence of a positive co-movement between the variables. However, this preliminary analysis does not take into consideration important econometric issues such as cointegration effects and nonlinear dynamics amongst the data. Considering that both series are integrated of order I(1), the data can be considered for cointegration analysis.

COINTEGRATION ANALYSIS

In this section we present the results obtained from the cointegration analysis and table 4 presents the results for the long-run estimates. Note that along with the PMG estimator we also present the estimates from the panel ordinary least squares (POLS) models, fixed effects POLS (FE-POLS), random effects POLS (RE-POLS), fully modified POLS (FM-POLS) and dynamic POLS (D-POLS) estimators. The obtained long-run coefficients produce estimates which range from as high as 2.38 (FE-POLS) to as low as 0.20 (PMG) and it is important to note that these are statistically significant at all critical levels. Overall, these estimates fall in

TABLE 3 Descriptive Statistics

Item	GDP	NTL
Mean	41.95347	79.87134
Median	15.61398	25.57545
Maximum	833.2920	1685.208
Minimum	0.427544	0.190523
Std. Dev.	98.46180	234.4203
Skewness	4.822411	5.412865
Kurtosis	28.72450	32.43515
Jarque-Bera	26417.04	34426.85
Probability	0.00	0.00
Sum	35240.92	67091.93
Sum Sq. Dev.	8133875	46105471
LLC (levels)	−1.78	5.79
LLC (1st differences)	−4.09***	−3.73***
IPS (levels)	5.49	6.04
IPS (1st differences)	−4.57***	−8.45***
Correlation with GDP	1	0.8
Observations	840	840

NOTES *** Rejection of HO at 10% significance level.

TABLE 4 Long Run-Estimates

Estimator	Coefficient estimate	*t*-stat	*p*-value
POLS	0.33	36.94	0.00***
FE-POLS	1.01	19.56	0.00***
RE-POLS	0.53	18.75	0.00***
FM-POLS	2.58	12.09	0.00***
D-POLS	0.35	39.26	0.00***
PMG	0.20	5.09	0.00***

NOTES *** Rejection of HO at 10% significance level.

the range of those obtained in previous literature (Nonso 2015; Otchia and Asongu 2020).

Table 5 presents the short-run and error correction cross-sectional results obtained from PMG estimators for the individual African countries. Note that in order for there to be a significant GDP night light cointegra-

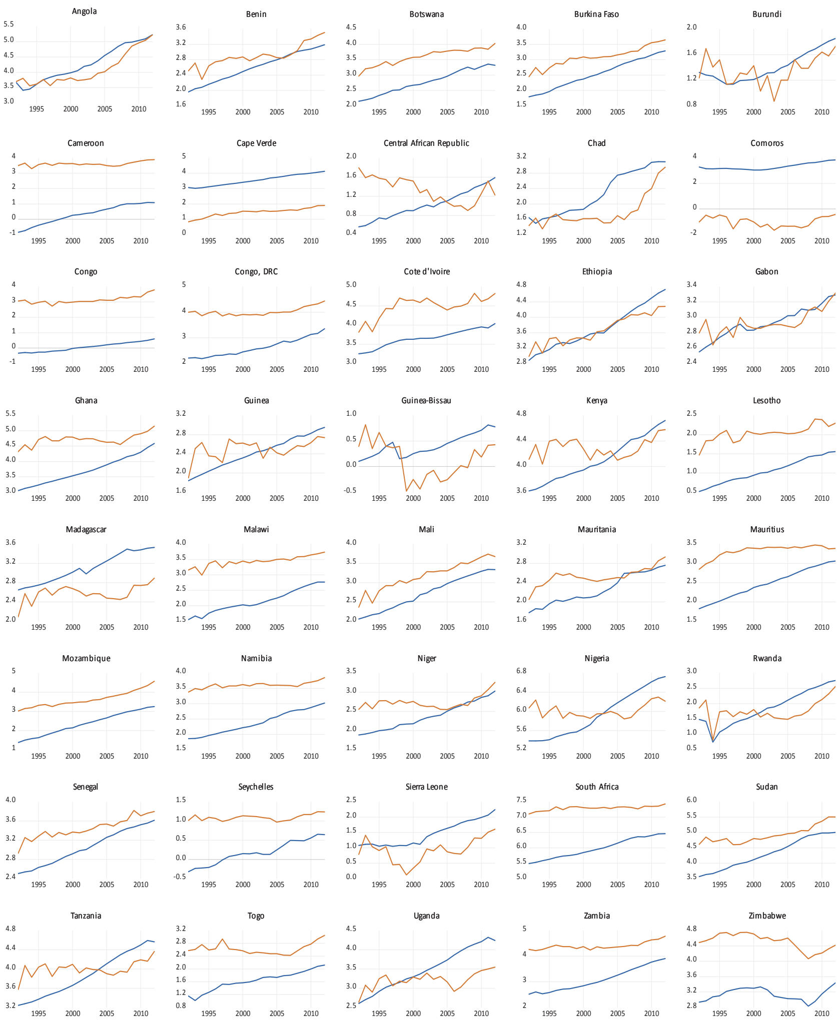

FIGURE 1 Individual Country Plots per Variable, 1992–2012 (blue – LGDP, red – Lnighttimelights)

tion relationship there must exist a negative and significant coefficient estimated on the error correction term (ECT) and a positive and significant estimate on the NTL coefficient. For the sake of convenience, in table 5 we highlight in bold the countries which satisfy these two conditions and find that only 16 countries out of the 49 countries satisfy the criteria (Angola, Benin, Burkina Faso, Burundi, Comoros, Côte d'Ivoire, Gabon, Guinea, Mauritania, Nigeria, Rwanda, Senegal, Sierra

TABLE 5 PMG Short-Run Cross-Sectional Estimates

Country	ECT			ΔNTL		
	(1)	(2)	(3)	(1)	(2)	(3)
Angola	−0.02	−36.92	0.00***	0.07	6.10	0.01**
Benin	−0.01	−153.81	0.00***	0.02	47.68	0.00***
Botswana	−0.03	−71.93	0.00***	−0.34	−23.35	0.00***
Burkina Faso	−0.01	−45.46	0.00***	0.07	23.53	0.00***
Burundi	−0.01	3.82	0.03**	0.07	80.15	0.00***
Cameroon	−0.06	−148.95	0.00***	−0.03	−6.00	0.01**
Cape Verde	−0.01	−147.09	0.00***	−0.06	−50.77	0.00***
Central African Rep.	0.04	40.55	0.00***	0.05	22.61	0.00***
Chad	0.00	−1.86	0.16	−0.17	−13.91	0.00***
Comoros	−0.02	−16.33	0.00***	0.03	61.40	0.00***
Congo	0.04	70.01	0.00***	0.03	13.62	0.00***
Congo, DRC	0.05	36.75	0.00***	0.30	19.83	0.00***
Côte d'Ivoire	−0.04	−38.24	0.00***	0.09	57.29	0.00***
Ethiopia	0.03	69.48	0.00***	0.03	5.04	0.02*
Gabon	−0.03	−12.62	0.00***	0.04	5.81	0.01**
Ghana	0.05	240.11	0.00***	0.02	14.36	0.00***
Guinea	−0.01	−63.70	0.00***	0.02	27.14	0.00***
Guinea-Bissau	0.08	−7.12	0.01**	0.01	1.34	0.27
Kenya	0.02	55.22	0.00***	−0.01	−9.98	0.00***
Lesotho	−0.01	−56.19	0.00***	−0.06	−43.03	0.00***
Madagascar	−0.02	−12.38	0.00***	−0.01	−3.27	0.22
Malawi	0.01	9.60	0.00***	0.26	40.23	0.00***
Mali	−0.01	−57.94	0.00***	0.00	1.23	0.31
Mauritania	−0.01	−7.48	0.01**	0.15	3.89	0.03*
Mauritius	−0.03	−196.27	0.00***	−0.16	−22.17	0.00***
Mozambique	0.00	24.00	0.00***	−0.28	−26.20	0.00***

Continued on the next page

Leone, Togo, Uganda, Zimbabwe). In further disseminating these results, we note that, in similarity to the findings by Keola, Anderson, and Hall (2015), a majority of the countries which find significant cointegration relationships between GDP and nigh tlight are those with higher shares of agriculture, forestry, and fishing in their GDP such as Benin

TABLE 5 *Continued from the previous page*

Country	ECT			ΔNTL		
	(1)	(2)	(3)	(1)	(2)	(3)
Namibia	0.02	57.94	0.00***	−0.13	−14.02	0.00***
Niger	0.05	87.03	0.00***	0.00	0.62	0.58
Nigeria	−0.01	−42.80	0.00***	0.09	46.82	0.00***
Rwanda	−0.07	−79.85	0.00***	0.49	252.82	0.00***
Senegal	−0.01	−14.75	0.00***	0.02	6.02	0.01**
Seychelles	−0.02	−8.27	0.00***	−0.12	−2.83	0.07*
Sierra Leone	−0.04	−26.30	0.00***	0.14	39.78	0.00***
South Africa	−0.02	−71.71	0.00***	−0.16	−21.87	0.00***
Sudan	−0.01	−44.68	0.00***	−0.05	−7.07	0.01**
Tanzania	−0.02	−36.54	0.00***	−0.05	−20.50	0.00***
Togo	−0.11	−228.45	0.00***	0.28	100.52	0.00***
Uganda	−0.03	−78.69	0.00***	0.02	5.52	0.01**
Zambia	0.06	102.58	0.00***	−0.11	−7.20	0.01**
Zimbabwe	−0.20	−17.76	0.00***	0.45	17.56	0.00***

NOTES Column headings are as follows: (1) coefficient estimate, t-stat, p-value. *, **, and *** denote 1%, 5% and 10% significance levels, respectively.

(27.11%), Burkina Faso (18.40%), Burundi (28.45%), Comorros (36.70%), Cote d'Ivoire (21.39%), Guinea (23.67%), Mauritania (20.19%), Nigeria (24.14%), Rwanda (26.25%), Senegal (17.03%), Sierra Leone (54.49%) Togo (18.78%), Uganda (23.93%) all which are above the SSA average of 18.51%. Interestingly, most of these identified countries heavily rely on fishing activities for livelihood and Li et al. (2021) recent showed that fishing activities can be easily captured from outer space using nightlight data. Furthermore, we observe that oil-rich countries, particularly, Angola, Gabon, Guinea, and Nigeria, tend to have more significant GDP nightlight relationships and this finding is not surprising since, as recently noted by Maldonado (2022), oil-rich regions tend to exert more luminosity compared to non-oil producing regions.

Moreover, our findings resonate with those Nordhaus and Chen (2012; 2015), who find that countries with worse (better) of data quality tend to have stronger (weaker) GDP-night light relationships. Based on the data quality grading system presented in Nordhaus and Chen (2012; 2015) as adopted from Summers and Heston (1988), there are 9 African countries with higher quality data (i.e. Botswana, Cameroon, Cote d'Ivoire, Kenya, Morocco, Senegal, South Africa, Tanzania, Tunisia and Zimbabwe) and out of these countries only Cote d'Ivoire and Zimbabwe reported significant cointegration relationships. The remaining 14 countries which find significant relationships (i.e. Angola, Benin, Burkina Faso, Burundi, Comoros, Gabon, Guinea, Mauritania, Nigeria, Rwanda, Senegal, Sierra Leone, Togo, Uganda, Zimbabwe) have poor data quality.

WAVELET COHERENCE ANALYSIS

In this section of the paper, the findings from the wavelet coherence analysis for the individual African countries are reported in the form of wavelet coherence plots which are essentially 'heat-maps' depicting the time-frequency correlation between GDP and night light intensity. The time domain on the wavelet coherence plots is measured along the horizontal axis whilst the frequency components are measured along the left-hand side of the horizontal axis with cycles ranging from 0 to 32 years. Note that the colour contours within each heat map measure the strength of the co-movement between the series, ranging from cooler colours (weaker correlations) to warmer colours (stronger correlations). The colour scales corresponding to the correlation strength are provided on the right side of each wavelet plot. The 5% significance level is represented by the faint white lines surrounding the colour contours whilst the inverted cone shape is the 'cone of influence' which accounts for edge effects.

Further note that the arrows contained within the colour contours describe the phase dynamics between the series which provides information on the direction of correlation (positive or negative) and the direction of causality. On the one hand, the series are considered in-phase or positively correlated with GDP leading (lagging) night light intensity if the arrow orientations are ↑, ↗, and → (↘), whilst on the other hand, the series are considered anti-phase or negatively correlated with GDP leading (lagging) night light intensity if the arrow orientations are ↓, ↙, and ← (↖).

From the wavelet coherence plots reported in the appendix, we group the findings from the individual countries into three categories. Firstly, there are 11 countries which produce in-phase correlations (positive) throughout the entire sample periods (Burundi, Central African Republic, Côte D'Ivoire, Democratic Republic of Congo, Ethiopia, Ghana, Mauritius, Nigeria, Sierra Leone, Togo, Zimbabwe). Secondly there are

10 countries which find in-phase through some or a majority of the time period (Cape Verde, Congo, Gabon, Guinea, Guinea-Bissau, Lesotho, Mali, Malawi, Rwanda, Zambia) Thirdly, there are 17 countries which either find predominantly anti-phase (negative) or insignificant correlations between the time series (Angola, Benin, Botswana, Burkina Faso, Cameroon, Comoros, Chad, Kenya, Madagascar, Mozambique, Namibia, Niger, Seychelles, South Africa, Sudan, Tanzania, Uganda).

It is also interesting to note that most African countries which have found significant time-frequency co-movements between GDP and nightlight data are countries which have faced civil wars during the period of observations (i.e. Burundi civil war (1993–2005), CAR bush war (2004–2007), Ivorian civil war (2002–2007; 2010–2011), DRC war (1996–2003), Ethiopia (various), Nigeria (Boko Haram conflicts since 2009), Sierra Leone civil war (1991–2002)) and these periods of conflict are dominated by high frequency oscillations in the wavelet plots. As observed by Witmer and O'Loughlin (2011) nightlights can be used to trace wars and conflicts, particularly where there are large fires that burn for weeks and large refugee movements. Moreover, Li and Li (2014) note that nighttime light and lit areas tend to decline (recover) during periods of conflict (peace) which correspond to declining (recovering) economic performance.

In further comparing the findings from the wavelet coherence analysis with those obtained from the PMG estimators, we find that only 6 countries commonly establish a significant relationship between night light intensity and GDP (Burundi, Côte D'Ivoire, Nigeria, Sierra Leone, Togo, Zimbabwe). In further comparing the results found in our study with previous literature, we conclude that our findings are not as optimistic as those obtained in previous African and international literature and only a few African countries find significant relationships between the variables from a cointegration and time-frequency perspective.

Conclusions

So, is it a bright idea to use country-specific night light luminosity as a proxy for economic growth in African countries? To answer this question, our study employs PMG estimators and wavelet coherence analysis applied to GDP and DMSP-OLS night light intensity data for 49 African countries to examine the cross-sectional cointegration relationship and time-frequency co-movements between the variables. On the one hand, the PMG estimators identify 16 out of the 49 countries which find significant positive cross-sectional cointegration effects between the night light and GDP, whilst on the other hand, the wavelet coherence identifies 11 out of the 49 countries which show positive synchronization between the variables across a time-frequency domain. And if these results are further narrowed down, we find that only 6 countries mutually establish significant relationships between PMG estimators and wavelet coherence analysis.

Altogether our study concludes that only very few African countries are at liberty to use regression analysis to create reliable synthetic GDP time series using DMSP-OLS night light intensity. Although our findings show little evidence of country-specific relationships between night light intensity and GDP for African countries, we do not refute the use of nighttime data as a proxy.

Instead, we propose two avenues for future research to reconcile the differences in empirical findings. Firstly, future studies could consider creating hybrid measures of economic growth using both night light intensity and other satellite imagery data such those capturing biodiversity, land cover and vegetation change which is more relevant for African countries whose economic output is highly dependent on fishing, farming and agriculture production. Secondly, future studies can focus on other sources of night light intensity data such as the Visible Infrared Imaging Radiometer Suite (VIIRS) day-night band (DNB) database which has luminosity time series in quarterly frequency and spans longer than the DMSP-OLS data.

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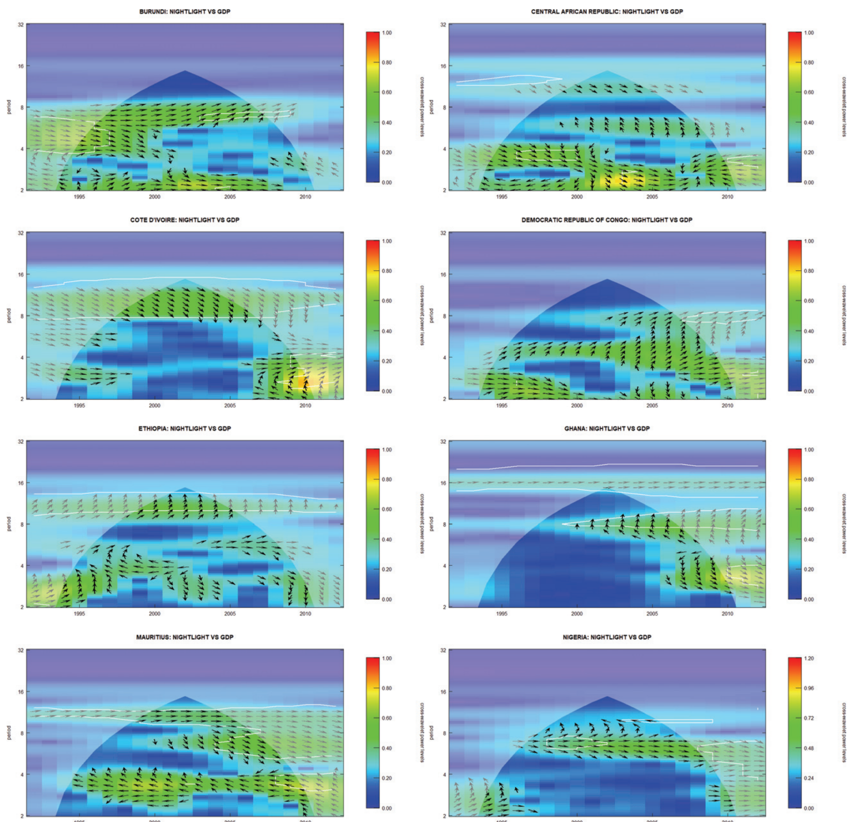
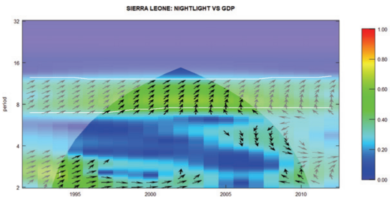
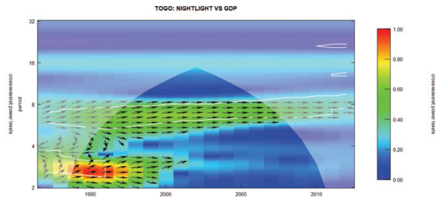
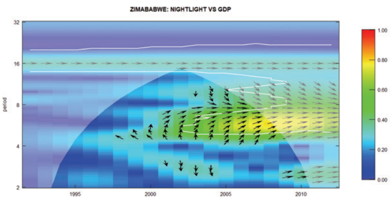
Appendix A

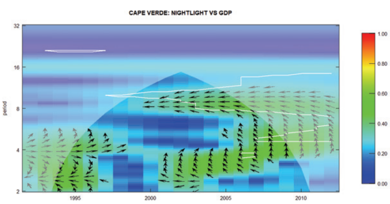


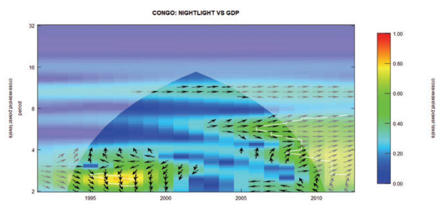

SIERRA LEONE: NIGHTLIGHT VS GDP

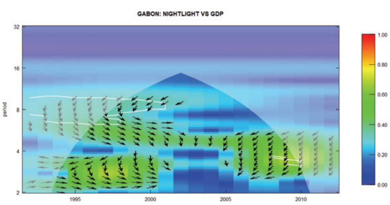

TOGO: NIGHTLIGHT VS GDP

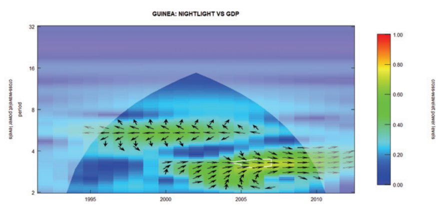

ZIMABABWE: NIGHTLIGHT VS GDP

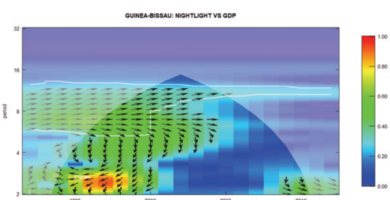
Appendix B

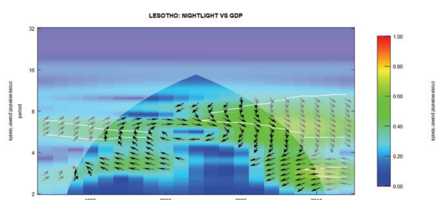

CAPE VERDE: NIGHTLIGHT VS GDP

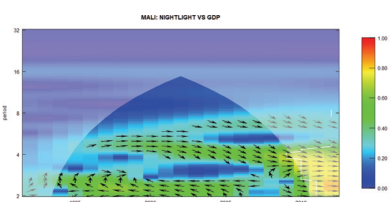

CONGO: NIGHTLIGHT VS GDP

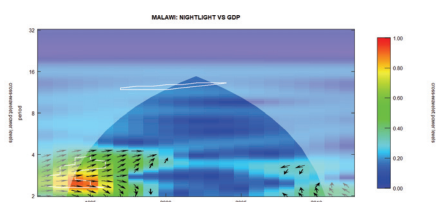

GABON: NIGHTLIGHT VS GDP

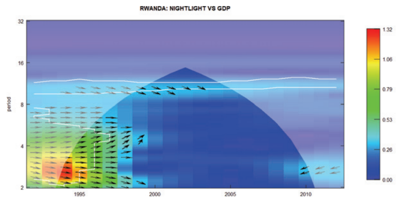

GUINEA: NIGHTLIGHT VS GDP

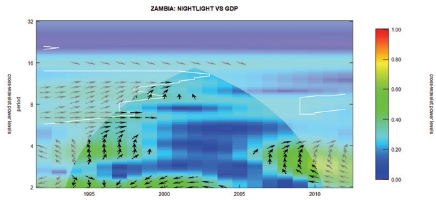

GUINEA-BISSAU: NIGHTLIGHT VS GDP


LESOTHO: NIGHTLIGHT VS GDP

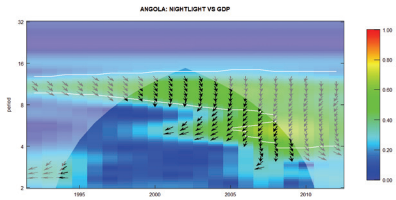

MALI: NIGHTLIGHT VS GDP

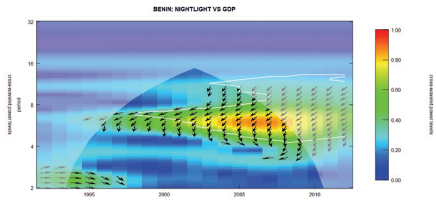

MALAWI: NIGHTLIGHT VS GDP

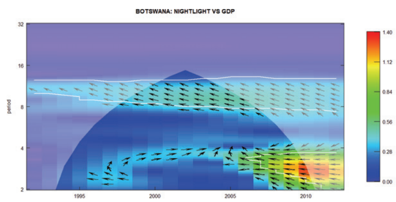

RWANDA: NIGHTLIGHT VS GDP

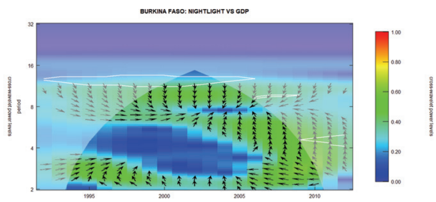

ZAMBIA: NIGHTLIGHT VS GDP

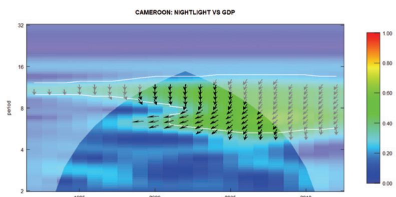
Appendix C

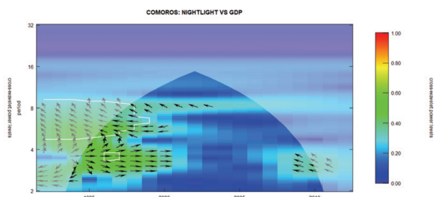

ANGOLA: NIGHTLIGHT VS GDP

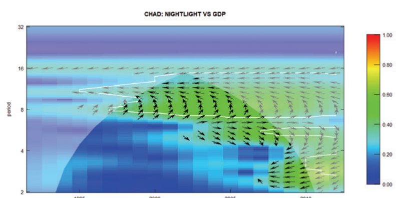

BENIN: NIGHTLIGHT VS GDP

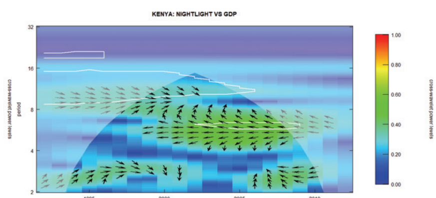

BOTSWANA: NIGHTLIGHT VS GDP

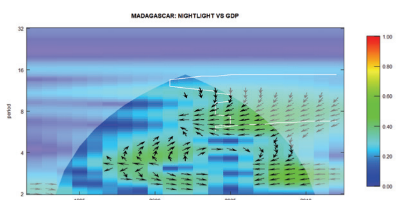

BURKINA FASO: NIGHTLIGHT VS GDP

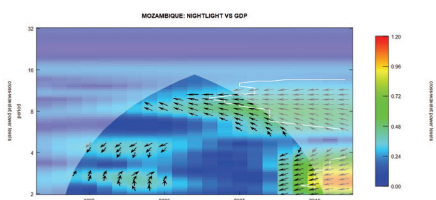

CAMEROON: NIGHTLIGHT VS GDP

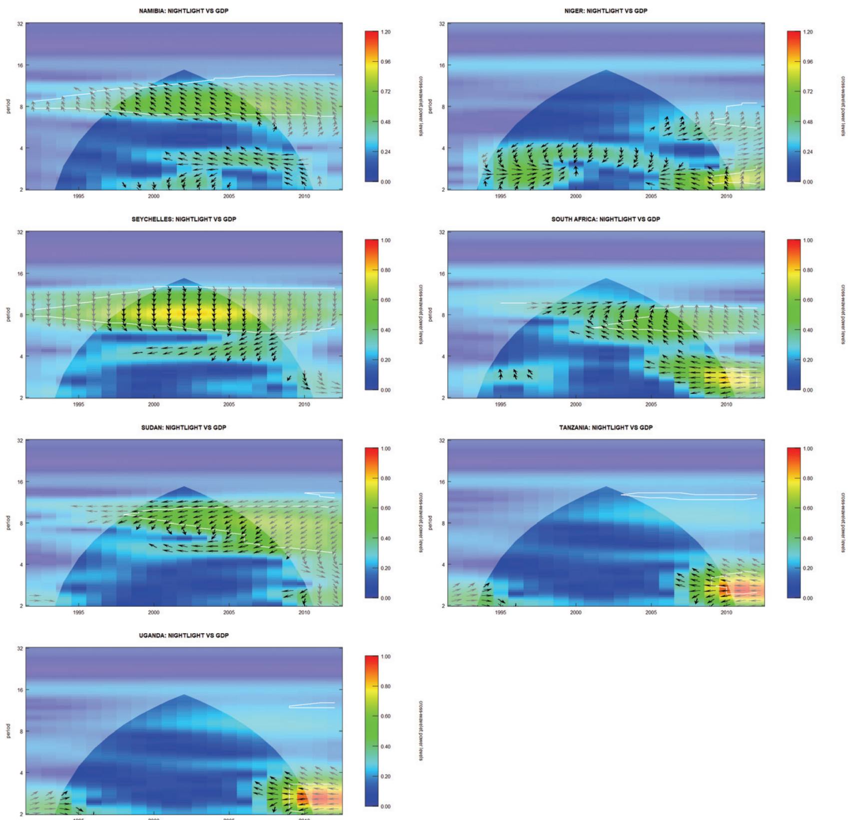

COMOROS: NIGHTLIGHT VS GDP


CHAD: NIGHTLIGHT VS GDP


KENYA: NIGHTLIGHT VS GDP


MADAGASCAR: NIGHTLIGHT VS GDP


MOZAMBIQUE: NIGHTLIGHT VS GDP


NAMIBIA: NIGHTLIGHT VS GDP
NIGER: NIGHTLIGHT VS GDP
SEYCHELLES: NIGHTLIGHT VS GDP
SOUTH AFRICA: NIGHTLIGHT VS GDP
SUDAN: NIGHTLIGHT VS GDP
TANZANIA: NIGHTLIGHT VS GDP
UGANDA: NIGHTLIGHT VS GDP
period
cross-wavelet power levels