top coding, while VIIRS can more consistently measure the radiance of light in a wider range of lighting conditions with higher accuracy (Elvidge et al., 2013; Gibson et al. 2021). In addition, VIIRS-DNB global cloud-free composites are available monthly, while DMSP global cloud-free composites are only available on an annual basis.

- Second, VIIRS data have higher spatial precision and temporal consistency (Gibson and Boe-Gibson, 2021). VIIRS nighttime lights data are more accurate, especially for less aggregated spatial units. For example, VIIRS from the Suomi NPP satellite crosses nearly every point on earth every night at around 1:30 am local time and takes high resolution photographs (Arderne et al., 2019). It has much better low-light detection capabilities with a dynamic range of seven orders of magnitude while DMSP has only two (Gibson, 2020). The VIIRS data have 45-times greater spatial resolution compared with DMSP (Elvidge et al, 2013). Gibson and Boe-Gibson (2021) used a 2001–2019 time-series of GDP for over 3000 U.S. counties as a benchmark to examine the performance of the VIIRS nighttime lights products as proxies for local economic activity, and disaggregated GDP data for various industries to examine the types of economic activity best proxied by night light data.

Monthly cloud-free VIIRS DNB Composite has two different versions of data.[2] The first uses a virtual cloud mask and is denoted as vcm. Data impacted by stray light are excluded from vcm. The second uses the virtual cloud mask and corrects for stray light and hence, is denoted as vcmsl. Some data impacted by stray light originally excluded in vcm is cleaned and added to vcmsl. Vcmsl has more data coverage toward the poles but will be of reduced quality. VIIRS composites are also available as annual composites. The annual VNL version 1 is simply a composite of the monthly vcm data with additional processing for ephemeral and background noise. In the annual composite version 2, a different filtering process is used as outlined in Elvidge et al. (2021). Using the county level data of the U.S., Gibson and Boe-Gibson (2021) argued that the vcmsl data, masked to zero out background noises, significantly improved the predictive performance compared with the DMSP data and unmasked VIIRS vcmsl data. In this study, we use the monthly vcmsl data as it is filtered to remove extraneous signals and because they are available at high frequency (monthly), meaning they offer the potential to extend the analysis to proxy these socioeconomic indicators at a more granular temporal level. Since GDP, CO2 emission, and electricity consumption are on an annual basis, yearly NTL composites were manually created by averaging over 12 monthly images.

Data Masking and Sums of Lights

The stray-light corrected version of nighttime light data used in this study are of 15 arc-second (~500 m at the Equator) spatial resolution and report averaged through the month daily observations of nighttime light radiance in nW/cm2/sr [VIIRS Nighttime Light Online Data][3]. A copy of the nighttime light data stored on Google Earth Engine databases [VIIRS Stray Light Corrected Nighttime Day/Night Band Composites Version 1][4] was used in this study for ease of performing analysis in Python software. While VIIRS data are available starting 2012, 2014 is the earliest period when the comparable VIIRS with stray-light corrected data are available. A collection of 8 annual images in all 54 countries in Africa from 2014 to 2021 were used to analyze the pre- and post-pandemic nighttime light dynamics.

To exclude from the analysis non-reliable nighttime light data, we performed procedures to filter out low cloud-free coverage and low average radiance following the methodology described in Elvidge et al. (2020).

[2] Source: VIIRS Nighttime Light (mines.edu)

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

[4] https://developers.google.com/earth-engine/datasets/catalog/NOAA_VIIRS_DNB_MONTHLY_V1_VCMSLCFG?hl=en#description

Thus, using the same filtering masks as in Lin and Rybnikova (2023), for every nighttime light image, pixels with: (i) =<2 cloud-free observations or (ii) =<0 nighttime light level, are excluded. Afterward, for each nighttime light composite, for each country, the numbers of the filtered-out pixels were calculated, and if a country had more than 5 percent of the original pixels filtered out, it was excluded from the analysis.[5] All data analysis was performed in Python. Data cleaning for individual images was performed prior to any computations.

Using the filtered nighttime light data, the sum of light (SOL) for each country and for each monthly nighttime light composite were calculated. For this sake, the latitude-adjusted nighttime light radiances of pixels within the administrative boundary of a state were summed up, following the methods of Elvidge et al. (2020). A scale of 500 m2, which is close to the VIIRS resolution of 463.83 meters, was used when calculating sums.

We developed a model to use nighttime lights to proxy GDP before the pandemic (2014-2019) and after the pandemic (2014-2021). Data on Gross Domestic Product (GDP, in constant US$2015) is from the World Bank World Development Indicators; CO_2 emission (Mton of CO_2 equivalent) is obtained from Emissions Database for Global Atmospheric Research; and electric power consumption (in billion kWh) is from the Energy Information Administration database. Building on the methodology developed in Lin and Rybnikova (2023), we used nighttime light to proxy GDP, CO2 emission, and electricity consumption. The model includes the following two steps:

First, we estimated the association between nighttime light and GDP during 2014 –2019 to identify the model in pre-pandemic years.

$$log\ \left(EconAct_{i,t}\right) = \alpha + \beta\ log\ \left(SoL_{i,t}\right) + \gamma Year_{adj} + \mu_i + \epsilon_{i,t} \tag{1}$$

where $EconAct_{i,t}$ stands for one of the three socio-economic activity indicators, including GDP, CO2 emission, and electricity consumption; $SOL_{i,t}$ stands for the sum of light, $Year_{adj}$ the year minus 2013 (so the series starts with a value 1 in year 2014), μ_i the time invariant state effects, and $\epsilon_{i,t}$ the error.

Second, we extended the model to include the year dummies in 2020 and 2021 accounting for the pandemic impact to examine the relationship between nighttime light and GDP, CO2 emission, and electricity consumption after the onset of the pandemic. In other words, in addition to the variables in the pre-COVID model, dummies *Y2020* and *Y2021* were added to capture the changes that affected the economic activity during the pandemic.

$$log\ \left(EconAct_{i,t}\right) = \alpha + \beta\ log\ \left(SOL_{i,t}\right) + \gamma Year_{adj} + sY2020 + tY2021 + \mu_i + \epsilon_{i,t} \tag{2}$$

where *Year2020* is the year dummy for 2020 (it equals 1 where year equals 2020 and it equals 0 in all other years), *Year2021* is the year dummy for 2021 (it equals 1 where year equals 2021 and it equals 0 in all other years).

Results

The application of the masks to account for the cloud influences on observations by filtering any pixels with a non-positive average radiance or less than three cloud free observations contributing to the radiance value enhanced the quality of the NTL data. Across the countries in Africa, out of the 432 data points (observations of eight years for 54 countries), 79 (or about 18%) outliers were dropped and 353 data points remained. Most of the extreme outliers are in 2014 -2016 while no data points were dropped in 2017-2020. The outliers spread across 40 countries, where a total of three data points were dropped in 12 countries each, two data points were dropped in 15 countries each, and one data point was dropped in 13 countries each.

The regression results of the associations between NTL and GDP, between NTL and CO2 emission, and between NTL and electricity consumption for a panel for the 54 countries from 2014 to 2019 and those for

[5] Data points with high percentages of pixels dropped were likely heavily affected by cloud or other noise, which could limit their reliability.

a panel from 2014 to 2021 are represented in Table 1. The regression results of the association between NTL and GDP for the pre-pandemic years 2014-2019 and for the whole period of 2014-2021 are represented in the columns (1) and (2) of Table 1, and those between NTL and CO2 emission in the columns (3) and (4), and those between NTL and electricity consumption in the columns (5) and (6), respectively.

- The results in columns (1) (3) and (5) showed that, in the pre-pandemic period of 2014-2019, the SoL is positively associated with GDP ($t=2.01$, $p<0.05$), with CO2 emission ($t=2.16$, $p<0.01$), and with electricity consumption ($t=2.41$, $p<0.01$), all in a significant manner. The positive signs of the coefficient of the adjusted year indicated a positive association with an increasing trend of GDP, CO2 emission, and electricity consumption over years.
- The results in columns (2) (4) and (6) showed that, in the whole period of 2014-2021, when COVID effect is controlled for using year dummies (Y2020 and Y2021), the SoL remained positively associated with GDP ($t=3.60$, $p<0.1$), with CO2 emission ($t=3.52$, $p<0.01$), and with electricity consumption ($t=2.80$, $p<0.01$), all in a significant manner. The positive sign of the coefficient of the adjusted year remained. As expected, the coefficient of the year dummies Y2020 and Y2021 that capture the impact of COVID are all negative and significant, except for Y2021 in column (4) for CO2 emission. This signals the prolonged large negative impact of the pandemic.

Table 1. Association between GDP, CO2, and electricity consumption and NTL before and after the COVID-19 pandemic in Africa (2014-19 and 2014-21)

Predictors and summary statistics	**Log(GDP), yy2014-19**	**Log(GDP), yy2014-21**	**Log(CO2) yy2014-19**	**Log(CO2) yy2014-21**	**Log(electricity) yy2014-19**	**Log(electricity) yy2014-21**
	Column (1)	Column (2)	Column (3)	Column (4)	Column (5)	Column (6)
Log(SoL)	0.030** (2.01)	0.056*** (3.60)	0.026*** (2.16)	0.048*** (3.52)	0.065** (2.41)	0.096*** (2.82)
Year adjusted	0.030*** (8.97)	0.026*** (7.45)	0.022*** (8.06)	0.019*** (6.20)	0.035*** (5.83)	0.033*** (4.20)
Year2020 dummy		-0.058*** (-4.45)		-0.034*** (-2.95)		-0.052* (-1.78)
Year 2021 dummy		-0.036** (-2.37)		-0.018 (-1.34)		-0.071** (-2.11)
Constant	22.895*** (132.45)	22.596*** (125.74)	2.517*** (17.97)	2.269*** (14.51)	-0.152 (-0.49)	-0.512 (-1.30)
R2 within	0.53	0.49	0.48	0.45	0.36	0.26
Number of obs.	241	342	240	341	248	353

Note: * $p<.1$; ** $p<.05$; *** $p<.01$. T-statistics in parentheses. The fixed effects estimations are applied following the results of the Breusch and Pagan LM test and Hausman test.

The goodness of fit of the regression models, as reflected by R squared, ranged around 0.45-0.55 for the associations between NTL and GDP and between NTL and CO2 emission, and around 0.26-0.36 for the association between NTL and electricity consumption. In the pre-pandemic period, around 53% of the variability observed in GDP, 48% of the variability observed in CO2 emission, and around 36% of the variability observed in electricity consumption are explained by the regression model with NTL and year as the independent variables. The goodness of fit is higher for the pre-pandemic period 2014-2019 than the whole period 2014-2021; and the difference is the largest for the association between NTL and electricity consumption where the magnitude of R squared is the lowest.

Discussion

This paper used the latest set of annual NTL composites from VIIRS/DNB from 2014 to 2021 to examine the relationship between NTL and economic and human activities – measured by GDP, CO2 emission, and electricity consumption in all countries in the African continent. Annual averages of nighttime light data were used to analyze the dimming of lights across the country as GDP, CO2 emissions, and electricity consumption were available annually. The NTL composites were filtered based on low cloud-free coverages and low radiance levels. The filtering helped zero out background areas where no lighting was detected and avoided poor data quality due to low numbers of observations. The application of masks helped filter the noises and enhance the reliability of the nighttime light data.

In the analysis, first, we examined the relationship of the latitude-adjusted NTL data, filtered on the low cloud-free coverage and low average radiances, with annual GDP, CO2 emission, and electricity consumption over the pre-pandemic period (2014 to 2019); and second, we extended the model to the pandemic time (2020 to 2021) with the additional year dummy of year-2020 and year-2021 to account for the COVID shock. The results showed that the association between NTL and GDP, CO2 emission, and electricity consumption are significant before and after the pandemic. The analysis adds value to the literature by using NTL to proxy these three indicators of human and economic activities in Africa. As the growth patterns, including recovery after external shocks, might vary across countries with different intensive of energy use and impact on the environment, the analysis of the association of NTL with GDP, CO2 emission, and electricity consumption can provide useful information to capture these trends at the subnational level with higher time frequency.

The statistically significant association between annual NTL and GDP, CO2 emission, and electricity consumption shed light on the potential to extend the analysis and use NTL to proxy more spatially disaggregated regional data, for example, for sub-national regions and cities/towns, and at a more granular temporal dimension, for example, the quarterly or monthly basis. This includes the possibility to trace the trajectories of economic growth and loss and recovery post external shocks using NTL to proxy GDP. Another possibility is to examine patterns of energy use efficiency and environmental impact by using NTL to proxy electricity consumption and CO2 emission and measure the energy use per unit of GDP and the CO2 emission intensity of GDP.

The model of using NTL to proxy human and economic activities can be particularly useful as some economic clusters might straddle regions or even spill across country borders. One example is the Brazzaville-Kinshasa cluster. The NTL data, which allow the "grouping" of economic clusters irrespective of the national lines, would enable the generation of information for these clusters which would otherwise not be feasible due to how data are collected and processed often by administrative units rather than economic clusters.

Conclusion

Satellite nighttime light data that measure the total amount of light produced at night have been used in the literature as a proxy for economic activity. This study developed a model to use nighttime light data to proxy GDP, CO2 emission, and electricity consumption in African countries. The empirical results showed that NTL is positively associated with each of these three indicators in a significant manner both before and after the pandemic.

This model can be applied to proxy GDP, CO2 emission, and electricity consumption at the subnational level at higher time frequency. This can help address the challenges faced in most countries, where traditional measures are lacking at the subnational level, infrequent, or inaccurate. For example, the most frequently used measure of economic activity, GDP, is only available at the national level annually in most African countries. Often, these numbers come with a delay of several months, while others might be inaccurate due to capacity constraints or political manipulation.

The methodology of using NTL to measure changes in economic activities can be applied to other contexts as well. Since VIIRS data span almost the entire globe and are available monthly at high resolution and accessible free of charge with only a short time lag, the methodology can be used to fill information gaps, including in countries with limited availability of economic statistics. The consistency of the VIIRS NTL can even potentially offer a solution of developing a measure to proxy economic activities across countries with different capacity in collecting and processing data as the seminal paper by Henderson et al (2012) indicated. Meanwhile, the results of the analysis should be interpreted with caution as the relation between NTL and GDP is conditioned by many factors, including indoors versus outdoors lighting, contributions of investment versus income, and the energy/light intensity of different productive activities.

Future research can further improve the quality of the NTL data and the consistency of the estimated relationship between NTL and GDP, CO2 emission, and electricity consumption. The first will involve enhancing the technology of satellite remote sensing to improve quality of the NTL imagery as well as better filtering background noise of the VIIRS data through masking. The second will focus on exploring suitable variables of control, such as production structure, urbanization, population density, and the patterns of energy use, to capture the difference of relations between NTL and these socio-economic indicators in different localities to improve the estimates. Since VIIRS data span almost the entire globe and are available monthly at high resolution, they can be used to fill information gaps and contribute to decision making for businesses and governments, including providing more granular information of the changes in economic activities at the subnational level in a timelier manner and providing an alternative of consistent measure for countries with limited availability of economic statistics.

Limitations

Light usage at night typically increases as income grows and the use of energy rises but the relationship between satellite data and socio-economic activities is complex, depending on many factors such as the production structure and efficiency of energy use. In addition to the pandemic, other factors, such as droughts, floods, and conflicts, may have a large impact on society and economy. Therefore, the results should be interpreted with caution.

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