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Noisy Night Lights Data:

Effects on Research Findings for Developing Countries

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Abstract

Night lights data are increasingly used by economists, especially for developing country research. Many of these countries have limited capacity to generate timely and accurate sub-national statistics on economic activity so satellite data seem attractive. Most studies have used Defense Meteorological Satellite Program (DMSP) data that are flawed by blurring, lack of calibration, and top- and bottom-coding. These noisy data are only weakly related to traditional economic activity measures for lower levels spatial units. More accurate data from VIIRS (the Visible Infrared Imaging Radiometer Suite) are available since 2012 but are rarely used by economists. This paper examines how recent published findings for developing countries based on DMSP data for very small spatial units change when the more accurate VIIRS night lights data are used. Our first example finds that economic activity is far more concentrated in low-lying, flood-prone, urban areas than is apparent with the DMSP data. Our second example shows that urbanization, as proxied by night lights, is not *ceteris paribus* associated with better child nutritional outcomes in Nigeria, contrary to claims in a study using DMSP data. In both examples, spatially mean-reverting errors in the DMSP data cause econometric bias that distorts policy implications.

Keywords

Anthropometrics
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JEL Classification

C80
O12
Q54

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I. Introduction

Satellite-detected night lights data are increasingly used in economics, especially for research on developing countries. Many of these countries have limited statistical capacity and their high reliance on agriculture and informal sector activities also makes accurate and timely measurement of economic activity difficult (Angrist et al, 2021). Consequently, data that are not subject to on-the-ground constraints, such as observations coming from satellites, can seem especially attractive to researchers working on developing countries. Most studies in economics using satellite-detected night lights rely on a data source—the Defense Meteorological Satellite Program (DMSP)—that was not designed with economists in mind, and instead was designed to detect clouds for short-term Air Force weather forecasts. Despite this provenance, early and influential evaluations noted that even though DMSP data may be noisy measures of true luminosity, they can serve as an adequate proxy for economic activity at the national level and the supra- and sub-national level (Henderson et al, 2012).

However, recent studies provide more grounds for caution in using DMSP data, especially in contexts of interest to development economists. First, there is now evidence of mean-reverting measurement errors in these data, so contrary to the case for random errors, coefficients will be biased if lights data are on the left-hand side of regression models and response coefficients may be exaggerated rather than attenuated if lights are on the right-hand side (Gibson, 2021). Much of the mean-reverting error is due to blurring of the DMSP images which is an inherent feature of DMSP sensors and data management (Abrahams et al, 2018). Earlier views that blurring was due to ice or water (Michalopoulos and Papaioannou, 2014) would naturally limit this problem to only a few places. Second, it is increasingly apparent that changes in DMSP data poorly predict changes in economic variables at the local level, even where they predict well cross-sectionally (Asher et al, 2021, Goldblatt et al, 2020; Nordhaus and Chen, 2015), which may limit usefulness of these data for impact evaluations.

A third reason for concern is that several recent uses of DMSP data are for very local levels such as sub-districts or even individual pixels (Gibson et al, 2020). Some detail on this trend for development economics is given in Table 1, for articles published in 2019 or 2020 in three journals: *Journal of Development Economics* (*JDE*), *World Bank Economic Review* (*WBER*), and *American Economic Journal: Applied Economics* (*AEJ:AE*). The spatial units in these studies range from the second sub-national level (districts) down to the individual pixel level. Except for Goldblatt et al (2020), who evaluate DMSP data at Vietnam's third sub-national level, these are not methodological data reliability studies, and instead rely on DMSP data for estimating causal impacts. This trend towards using DMPS data to study very local level economic activity matters because DMSP data do worse at predicting conventional economic activity measures, such as sub-national GDP, for lower level spatial units, for lower density areas, and for more agricultural areas in developing countries (Gibson et al, 2021). Yet studies such as Gennaioli et al (2014) that are cited to support using DMSP data to proxy for local economic activity are mainly for larger sub-national units. The flaws in the DMSP data are less visible when working with these more aggregated spatial units.

Table 1: Details on Recent Studies Using DMSP Data as a Proxy for Local Economic Activity in Analyses on Developing Countries

Authors	Journal/Year	What is being evaluated?	Spatial Unit	Time Period
Dreher et al	*JDE*, 2019	Impact of African leader's birthplace on the receipt of Chinese foreign aid	1650 aid projects geocoded to district level in 47 African countries	2000-2012
Eberhard-Ruiz et al	*JDE*, 2019	Impacts of regional economic community on economic growth of border cities	180 cities in 3 East African countries	1992-2013
Heger & Neumayer	*JDE*, 2019	Impacts of Boxing Day tsunami and reconstruction aid on economic growth	276 sub-districts in Aceh, Indonesia	2003-2012
Mamo et al	*JDE*, 2019	Impacts of mining (intensive and extensive margins) on local economic development	3635 districts in 42 African countries	1992-2012
Prakash et al	*JDE*, 2019	Impact of electing criminally accused politicians on economic performance of their constituency	2633 State Assembly constituencies in India	2004-2008
Jagnani & Khanna	*JDE*, 2020	Impact of opening elite public colleges on the provision of public goods in nearby areas	453,921 villages in India	2004-2012
Amare et al	*WBER*, 2020	Impact of urbanization on anthropometric indicators for young children	DMSP pixels at reported coordinates of DHS survey clusters in Nigeria	2008 and 2013
Goldblatt et al	*WBER*, 2020	Evaluate performance of DMSP night lights and Landsat daytime imagery for predicting levels of and temporal changes in employment, expenditure and enterprise counts	Third Sub-national level (communes) in Vietnam, n=5308 for panel analyses and n=7643 for a single year cross-section	2004-2012
Kocornik-Mina et al	*AEJ:AE*, 2020	(a) Examine concentration of economic activity in low-lying flood prone areas and (b) impact of 53 large floods (affecting 1868 cities in 40 countries) on local economic activity	3.64 million DMSP pixels (a) 0.24 million urban grid points at 30 arc seconds (≈0.9 km × 0.9 km) resolution (b)	2012 (a) 2003-2008 (b)

Notes: The Kocornik-Mina et al (2020) study is not restricted to developing countries but most of the large floods they study affected cities in developing countries in South and East Asia, and Africa so we include it here. The reported sample size for Amare et al (2020) is 560 DHS clusters but the description of the sample selection approach in their paper leads to a different sample size, as discussed in Appendix A.

A fourth reason for concern about DMSP data is that far more accurate night lights data are available since 2012 from the Visible Infrared Imaging Radiometer Suite (VIIRS) of instruments on the Suomi satellite. Experts on night lights data, such as Elvidge et al (2013), note that VIIRS is more spatially precise than DMSP, with at least 45-times greater resolution and no blurring, and can accurately measure radiance in lighting conditions that cover almost seven orders of magnitude while the DMSP range is far more limited. This greater accuracy of VIIRS data shows up as better detection of populated areas (Chen and Nordhaus, 2015), and predictive power for cross-sections of sub-national GDP is up to 80% higher than what is achieved with DMSP data (Gibson, 2021). It is especially for lower level spatial units, like counties, that VIIRS outperforms DMSP as a GDP predictor (Gibson et al, 2021).

The improvement offered by VIIRS is reflected in the scientific literature; since 2015 more articles per year publish using VIIRS night lights data than using DMSP data (Gibson et al, 2020). Economics is an outlier in this regard, with most studies on night lights continuing to use DMSP data and ignoring VIIRS; Gibson (2021) reviewed 41 economics articles and working papers from 2019 or 2020 that used night lights data, and over 90% of these used DMSP data. This on-going use of noisy night lights data raises the question of whether there are published economics findings that are unreliable, in the sense of having the results change substantively when the more accurate VIIRS night lights data are used. In other words, does it matter that economists persist in using DMSP data, in the practical sense of publishing findings with the DMSP data that may distort policy in developing countries.

The current paper attempts to answer this question, although we are limited in what we can study. Many economics studies using DMSP cover periods before VIIRS data became available in 2012, as can be seen from Table 1. We could focus on reported relationships between DMSP data and an outcome of interest that was estimated with data prior to 2012, and then extend that to the post-2012 period using the VIIRS data. However, a problem with this approach is that it does not rule out other reasons for estimated parameters changing, such as an evolution in lighting types that shifts the relationship between outcomes of interest and true luminosity. Instead, a more definitive answer may come from examining studies where at least some of the reported relationships can be estimated for 2012 or 2013, which are the years when DMSP and VIIRS overlap.[1]

Amongst the papers in Table 1, two allow some of their reported relationships to be examined with both DMSP data and VIIRS data for the same year. These papers are also notable for estimating relationships at the DMSP pixel level. It is as a proxy for very local economic activity that DMSP is most problematic as it is hard to distinguish a location from its surroundings with these blurred data. Conveniently for illustrating the generality of biases that come from using the DMSP data, one of these studies has DMSP data on the left-hand side (LHS) of regressions and one has it on the right-hand side (RHS) yet both have biases.

The first paper we examine is Kocornik-Mina et al (2020), who use pixel level DMSP data to estimate impacts of flooding on economic activity. While their main results are for the 2003-08 period, before the VIIRS data existed, they also use 2012 data to show how lights (as a proxy for economic activity) are concentrated in low-lying, flood-prone, urban areas. When we compare DMSP data and VIIRS data for the 3.6 million pixels they use for this regression we find a strongly mean-reverting error in the DMSP data. Thus, even though lights are the LHS variables in the regressions, the coefficients estimated using DMSP data are attenuated; rather than low-lying, flood-prone, areas having luminosity values 20% above national averages, the margin is 85% when using the more accurate VIIRS data. Evidently, the risks to economic activity posed by flooding are far greater than is shown by the DMSP data.

The second paper is Amare et al (2020), who relate Nigeria Demographic and Health Survey (DHS) child anthropometrics to DMSP night lights at the published coordinates of the survey enumeration areas. They report positive, statistically significant, relationships between standardized child height or weight and DMSP night lights and conclude that urbanization improves child nutritional outcomes.[2] In contrast, using VIIRS data with the same outcome and control variables that Amare et al (2020) use, we find child anthropometric outcomes generally worse, *ceteris paribus*, in areas with greater luminosity. These results suggest that it is unlikely that urbanization, *per se*, in countries like Nigeria has improved child nutritional outcomes.

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[1] Ghosh et al (2021) recently extended the DMSP time-series, using pre-dawn data from satellite F15 for 2014 to 2019 (readings from this satellite previously ended in 2007). This is feasible because of unstable orbits; DMSP satellites observe earth earlier as they age so what starts as Day-Night observation becomes Dawn-Dusk observation. Pre-dawn lights are more likely to come from public infrastructure (e.g. street lights) than from private consumption and production activities, so the extended DMSP time-series are inconsistent with the earlier, 1992-2013, series (Gibson and Boe-Gibson, 2021). Thus, we do not use these extended DMSP data.

[2] Amare et al (2020) do not correctly describe the rules used to form their estimation sample. There are also other issues that make their results non-reproducible, even when we solely use DMSP data. The discussion of these issues is relegated to Appendix A, as it is not central to our main message, which is about how results change when the more accurate VIIRS data are used instead of the noisy DMSP data.

II. Misinterpreting the Spatial Resolution of DMSP Night Lights Data

A common misunderstanding in economics is that sensors on DMSP satellites detect differences in night lights coming from areas of one km^2 or smaller. We bold and underline key verbs in the following quotes: "[T]hese images **<u>record</u>** average light output at the 30 arc second level, equivalent to about 1 km^2 at the equator" (Baskaran et al (2015: 66). Variants of this claim are repeated by several of the papers listed in Table 1, such as: "[L]ight intensity is **<u>measured</u>** at 30 arc second resolution (equivalent to 0.86 km^2 at the equator), on a scale [the Digital Number or DN] from 0 to 63" (Eberhard-Ruiz and Moradi, 2019: 258) and "[T]hese satellite-based remote sensors **<u>collect</u>** daily nighttime light intensity data from every location on the planet at about a one square-kilometer resolution" (Amare et al, 2020: 65).

It is true that data from the DMSP annual composites are *allocated* to output grids of 30 arc seconds.[3] However, the underlying sensor resolution is far coarser so it is wrong to say that light are *recorded*, *collected* or *measured* at a spatial resolution of 30 arc seconds. This may seem to be semantics but a better understanding of DMSP spatial resolution may help to prevent inappropriate uses of these data. A salient analogy for economists is with household survey data; these are often reported in *per capita* terms, yet the level of resolution at which it is feasible to collect the data (both for conceptual reasons, such as public goods within the household, and for practical reasons) is typically household level. Users of household survey data understand that the *per capita* data do not reveal individual consumption, so differences between individuals will be blurred (as the intra-household component of inequality is unobserved).[4] Likewise, differences between each of the 30 arc second DMSP output cells are blurred, as the data are collected from far bigger pixels.

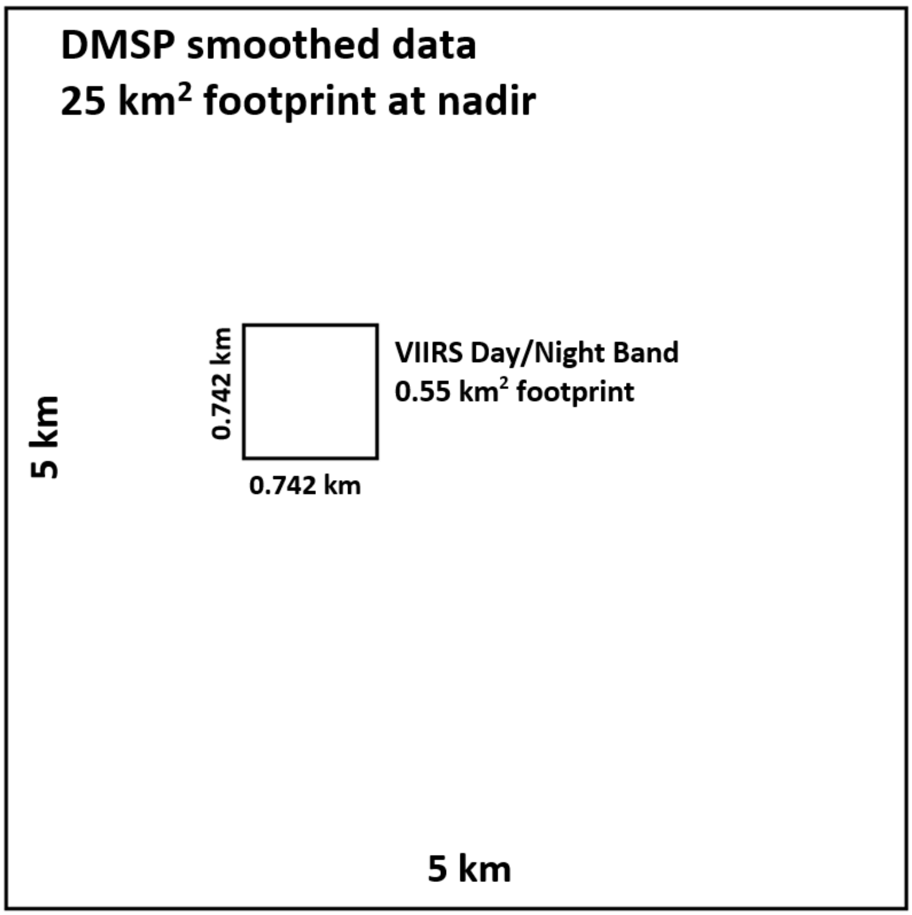
The DMSP data transmitted to earth are for pixels that are 5x5 blocks of the original ('fine') pixels; blocking is needed so as to conserve data storage. In the absence of geo-location errors these 5x5 blocks would cover about 7 km^2 (2.7 km×2.7 km) at the nadir of the 3000 km swath of the sensor. The pixel footprint gets 240% bigger at the edge of the half-swath, 750 km from the nadir, which is where NOAA set the limit for usable images (the footprint expands away from the nadir due to the angle of viewing the earth). The DMSP geolocation errors, which are discussed in the remote sensing literature for about a decade (Tuttle et al, 2013), further displace the signal by about three kilometers from where the light sources are located. Allowing for effects of the smoothed 5x5 blocks and for effects of the geolocation errors, night lights experts like Elvidge et al (2013) describe DMSP as having a 25 km^2 ground footprint at nadir. Given the expansion in pixel footprint away from the nadir, the pixel size could be as large as 60 km^2 at the edge of the half-swath.

A very clear diagram of the DMSP pixel footprint compared to the far smaller VIIRS footprint is presented in Elvidge et al (2013). Figure 1 provides a reproduction. This paper by

[3] This is equivalent to a grid of about 0.9 km×0.9 km at the equator or 0.9 km×0.7 km at 40 degrees of latitude.
[4] Deaton and Paxson (2000) provide an approach to recover individual consumption, by assuming households are a veil for the individuals within them. Extending the analogy, a similar approach would be to lift the veil on DMSP data to uncover differences in night lights at the 1 km^2 scale. See Abrahams et al (2018) for more detail.

experts on DMSP data is widely cited yet is largely ignored by economists using night lights data.[5] Elvidge et al (2013) show VIIRS greatly improves over DMSP in several dimensions. In terms of spatial resolution, VIIRS has a constant 0.55 km^2 footprint over its full sweep because the sensor compensates for the effect of viewing the earth at an angle (away from the nadir) by turning off some detector elements, with no need for onboard smoothing of pixels to conserve data storage and with no known geolocation errors. Once it is understood that the DMSP pixel footprint is at least 25 km^2 and that composing annual composites from selected nightly images does not provide a way to sharpen the image to a 1 km^2 resolution, some uses of DMSP data may seem misguided.

Figure 1: Ground Footprint for Night Lights Data Collected by DMSP and VIIRS



Source: Elvidge et al (2013) Figure 1, p.65

One way that the coarse resolution of the DMSP data shows up is with the far worse performance of DMSP as a proxy for economic activity, compared to how VIIRS performs, the smaller or more local are the spatial units being studied (Gibson et al, 2021). Essentially, it matters less that the DMSP pixel footprint is at least 25 km^2 rather than 1 km^2 if one is

[5] A *Google Scholar* search on 28 June, 2020 shows 336 citations. Just three are empirical papers in economics journals (Keola et al, 2015; Ameye and DeWeerdt, 2020; Ch et al, 2021) A further two citations are to review articles in economics journals (Donaldson and Storeygard, 2016; Michalopoulos and Papaioannou, 2018).

aggregating the night lights data to the national level or the first sub-national level (provinces or states) compared to when the lights data are being used for smaller and lower level units like counties or sub-districts. Another way to debunk the idea that DMSP data can distinguish differences in night lights for areas as small as 1 km^2 is to simply look at the maps of what is, ostensibly, lit area. For example, Gibson (2021) shows that a fairly rural area, Oxfordshire in the United Kingdom, seems almost entirely covered in lights with DMSP data, where separate small towns appear as one big lit area, and lit area of more isolated small towns is overstated by five-fold or more.[6] This feature where DMSP data attribute light to unlit areas reflects the pixel footprint having a resolution that is far coarser than the 1 km^2 level claimed by many.

Carrying on with the idea of simply looking at the data, Figure 2 has two maps of lit area for the same region (with the same scale and color scheme); one using DMSP and one VIIRS.[7] To allow some introspective ground-truthing, we map a region known to many development economists who may visit or work at the World Bank—Washington DC and environs. Specifically the area mapped ranges from Dulles Airport in the west to the Port of Baltimore in the east, and from Frederick in the north to Manassas in the south, which gives dimensions of about 100 km east-west and 80 km north-south. Given that many readers will have first-hand experience of this area, the maps provide a useful basis to illustrate some flaws in the DMSP data and particularly their coarse spatial resolution.

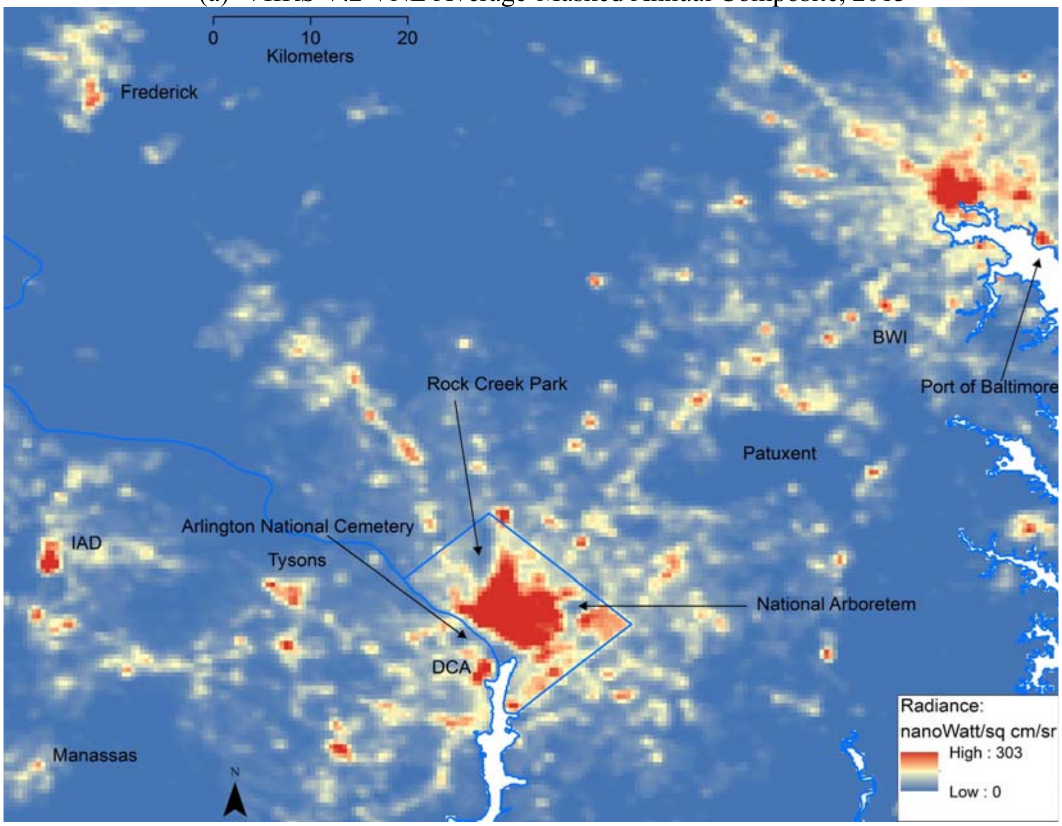
The VIIRS data clearly identify key infrastructure, such as the three main airports, Dulles (IAD), Reagan National (DCA) and Baltimore-Washington (BWI), and the Port of Baltimore. The light output recorded from these brightly lit areas ranges from 105 $nW/cm^2/sr$ for BWI to 165 $nW/cm^2/sr$ for IAD. The light output from brightly lit central areas of the two big cities (e.g. near Metro Center in Washington DC or in downtown Baltimore) ranges from 220-300 $nW/cm^2/sr$. Also, one can easily see outlying towns, such as along I-270 going northwest from near Bethesda to Frederick (these towns along I-270 have populations of over 50,000). Some of the tallest buildings in the area are clustered at Tysons (due to the height restrictions in Washington DC) which is clearly distinguishable from the surrounds.

Going to the other end of the luminosity spectrum, even within the District large areas have little light output, such as Rock Creek Park (six $nW/cm^2/sr$) or the National Arboretum (12 $nW/cm^2/sr$). Across the Potomac, Arlington National Cemetery is clearly darker than Rosslyn to the north or Pentagon City to the south. Further afield, the 50 km^2 area of the Patuxent Research Refuge clearly shows up as a large unlit area. More generally, most areas on the map show up as having only low levels of luminosity; 65% of pixels are as dark as the Arboretum ($\leq$12 $nW/cm^2/sr$). This is consistent with what is seen with other remote sensing data, such as for tree cover. According to the database from Hansen et al (2013), one half of the land area shown on the map had at least 30% tree cover (using 30 m Landsat pixels).

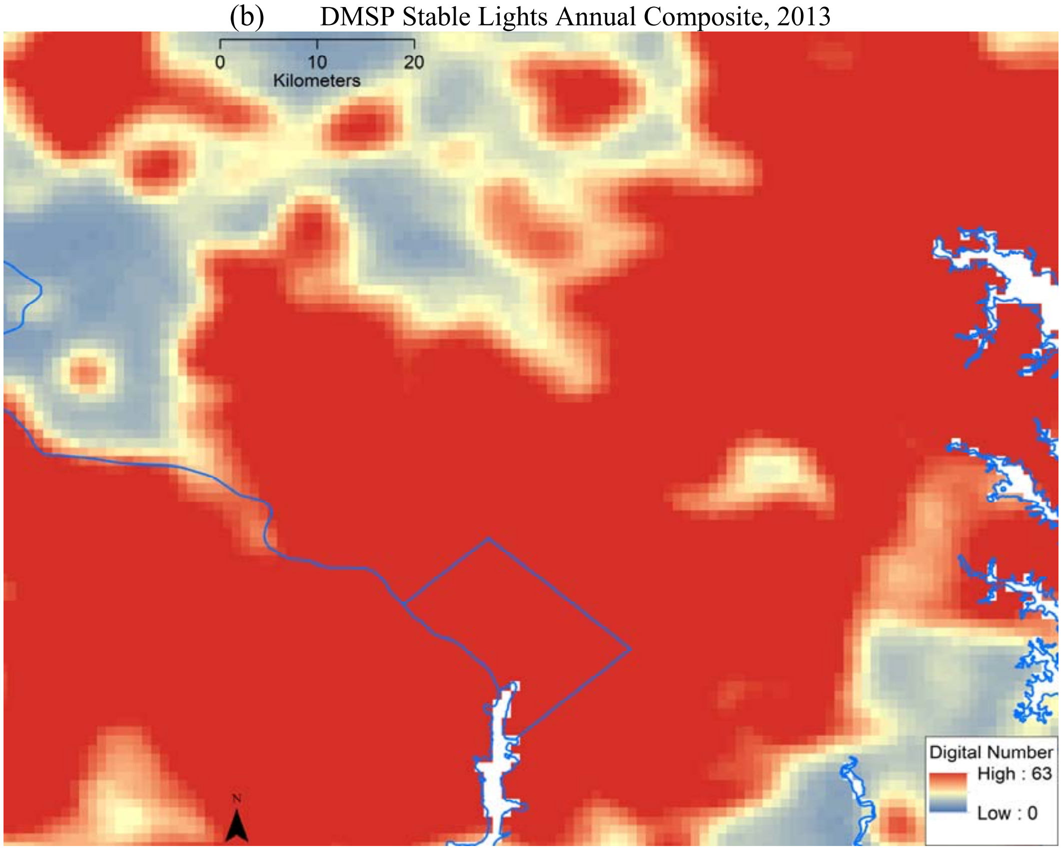
[6] At the time of the 2011 census just over 7% of Oxfordshire was built-up area according to ONS maps that can be accessed here: https://geoportal.statistics.gov.uk/datasets/f6684981be23404e83321077306fa837_0
[7] The images are for 2013. For DMSP we use data from https://eogdata.mines.edu/products/dmsp/#v4 and the VIIRS data are from https://eogdata.mines.edu/products/vnl/#annual_v2 (average-masked).

Figure 2: Illustrating Flaws in DMSP Night Lights Data: Washington DC and Environs

(a) VIIRS V.2 VNL Average-Masked Annual Composite, 2013



(b) DMSP Stable Lights Annual Composite, 2013



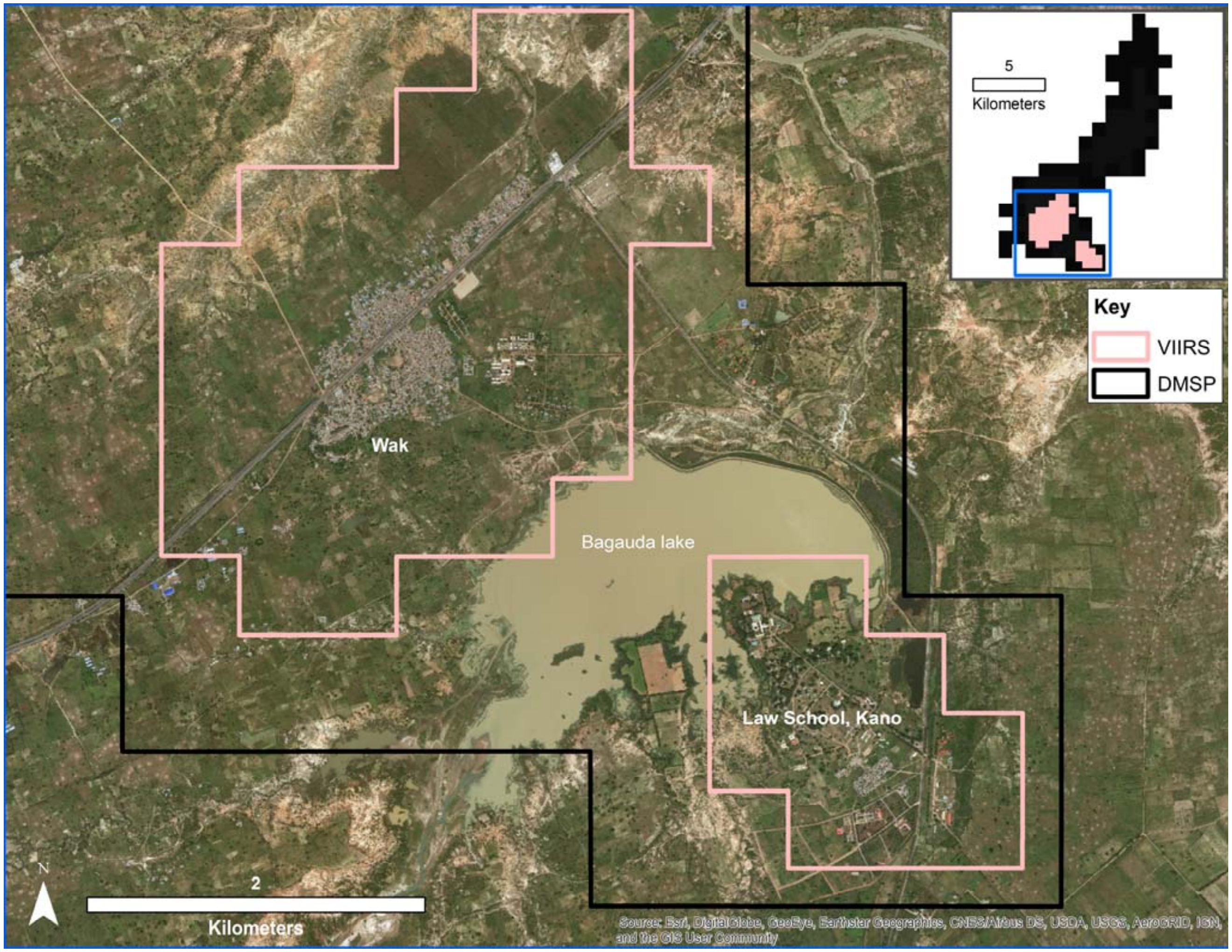
Unlike the spatial heterogeneity shown by the VIIRS data, DMSP data do not allow separate features to be distinguished and most of the area seems equally brightly lit. A small part of the map in the southeast corner near Chesapeake Bay has lower DN values, and some forested areas near Frederick and part of the Patuxent Refuge also have lower DN values.[8] Otherwise, the map is largely an undifferentiated blob of red denoting the highest DN values; almost two-thirds of the DMSP output pixels have DN values of 55 or above; the threshold used by Bluhm and Krause (2022) for identifying DMSP pixels likely to be top-coded. These DMSP data cannot distinguish brightly lit infrastructure, like IAD or the port of Baltimore, from nearby areas and their blurring hinders one from forming a precise sense of where cities stop and rural hinterland starts. A map like Figure 2b should debunk any thought that DMSP data measure differences in night lights coming from areas of one km^2 or smaller.

A potential objection that development economists may have to illustrating the coarse spatial resolution of DMSP data with images from rich country big cities is that night lights in developing countries may be quite different. One counter to this is that the same inability of DMSP data to distinguish key spatial features also shows up for developing country cities. For example, Gibson et al (2021) show DMSP data cannot identify the main port in Jakarta, despite it being clearly visible in VIIRS data. This port handles two-thirds of Indonesia's international goods trade and is the 22nd busiest container port in the world (just ahead of the port of New York City/New Jersey) and so it is a rather big thing to miss, from an economic standpoint. Moreover, Jakarta's port covers about 9 km^2 and so clearly exceeds the widely claimed 1 km^2 resolution of DMSP data and yet it cannot be identified with these data.

Figure 3 uses images for a low density area of a developing country to show that blurring of DMSP data is not restricted to cities. We map one of the six Nigerian Law School campuses, with dormitories and classrooms for about 1000 students situated in an isolated location beside Lake Bagauda (surface area of 2 km^2) in Kano State. On the other side of the lake the town of Wak has about 25,000 people. The rural hinterland has no concentrated sources of night lights. If DMSP data truly detect differences in lights for areas as small as 1 km^2 the two lit areas should show up separately and the remaining area would be unlit. The VIIRS data meet this standard; the Law School campus has 12 lit pixels (2.5 km^2) and Wak has 36 lit pixels (7.5 km^2), with no light recorded over the lake or from the rural hinterland.[9] In contrast, the DMSP data suggest a contiguous lit area of 78 km^2, including the lake and much of the rural hinterland, with no separation seen between the Law School and Wak township.[10] The Figure 2 and 3 maps show how untrue is the claim of DMSP data detecting differences in night lights for areas as small as 1 km^2 even though this claim is often repeated in economics journals.

[8] The maps are clipped using a land/water boundary layer, so apparent precision of DMSP in not having lights over water is misleading. In fact, pixels that are entirely on the Potomac or Chesapeake Bay have DN values of 59 and above (where 63 is the maximum), reflecting the inherent spreading of light in the DMSP data.
[9] At the latitude of Figure 3, the VIIRS output pixel size of 15 arc seconds covers approximately 0.21 km^2.
[10] This eight-fold overstatement of lit area when using the DMSP data is consistent with other evidence for small towns in Africa reported in Gibson et al (2020).

Figure 3: DMSP Cannot Distinguish Separately Lit Areas and Makes Unlit Areas Appear Lit: Nigerian Law School and Wak, Kano, Nigeria



Note: Lit area outlines are for 2013, with the black line for the edge of the contiguous area that DMSP indicates as lit and the pink lines show lit areas according to VIIRS. Inset map shows the full contiguous area that DMSP shows as lit, with blue frame showing the area mapped in more detail.

III. Night Lights and Flooded Cities

The first paper we examine to see if findings change when more accurate VIIRS night lights data are used in place of inaccurate, coarse resolution, DMSP data is Kocornik-Mina et al (2020).[11] This paper uses 3.64 million DMSP pixels in 2012, for a sample of almost 35,000 urban areas (mostly in developing countries), to regress the logarithm of the DN value on a proxy for being flood-prone; a dummy variable for being below 10 meters elevation. Other regressions also interact the low elevation dummy with a dummy for ever experiencing high precipitation events (>1000 mm rain in a month). The main goal of the paper is to estimate the impacts of 53 floods that occurred between 2003 and 2008 (so prior to VIIRS data being available) but the regressions for 2012 aim to highlight the potential economic importance of flooding due to the concentration of economic activity in low-lying urban areas.

Kocornik-Mina et al (2020) discuss two limitations of DMSP data: top-coding and bottom-coding, but ignore spatial imprecision. They write (p.47) that "[L]ight intensity can be mapped on approximately one-kilometre squares". This is better than saying *recorded*, *collected* or *measured* if we allow "mapped on" to refer to data being *allocated* to an output grid of 30 arc-seconds, but it gives no indication that the DMSP ground footprint is anywhere from 25 km^2 to 60 km^2. In terms of top-coding, they note DN=63 is top-coded but argue that most floods they analyse affect developing countries where much of the light activity is below the top-coded level. Yet Bluhm and Krause (2022) note that top-coding affects more pixels than just those with DN=63; the DMSP annual composites average over many nights so pixels top-coded some nights but not others have DN values below 63. Instead, Bluhm and Krause (2022) use a threshold of DN=55 for pixels potentially subject to top-coding. The replication data from Kocornik-Mina et al (2020) have 20% of DMSP pixels at DN=55 or above versus just 7% at DN=63. In terms of bottom-coding, Kocornik-Mina et al note that 5.5% of their DMSP pixels are coded zero, and they discard these when they take logarithms.

We used coordinates in the Kocornik-Mina et al (2020) replication files to get DMSP and VIIRS data for 2012 for the same points used in their Table 3 regressions. A few points lacked data in the downloads so our sample is slightly smaller; 3.638 million pixels versus their 3.642 million. For internal consistency of our results when comparing DMSP versus VIIRS we just use our sample rather than using their DMSP data from the replication files (differences in results using their DMSP data versus our DMSP sample only show up at the third decimal point). The first three columns of Table 2 repeat specifications in columns (1) to (3) of their Table 3, but with our DMSP data. The results suggest low-lying pixels have luminosity values that are about 20% higher than national mean values (with a standard error of 4.4 percentage points, using the approximate unbiased variance estimator of van Garderen and Shah, 2002), based on the specification using country fixed effects. With city fixed effects (in column (3)), the low-lying pixels have DN values that are about 6% higher than average.

[11] Data in this section are from https://eogdata.mines.edu/products/dmsp/#v4 for DMPS, and for VIIRS are from https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/products/VNP46A4/. For VIIRS we use the near-nadir snow-free composite, which should have the least blurring and shadow effects for urban areas.

Table 2: Measurement Errors in Night Lights Data and Apparent Relationships Between Elevation and Luminosity

Dependent variable	ln (DMSP DN value)			ln (DMSP DN value)		ln (VIIRS average annual radiance)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Elevation < 10 metres	0.183***	0.185***	0.059**			0.620***	0.624***	0.318***
	(0.037)	(0.037)	(0.027)			(0.083)	(0.083)	(0.078)
Elevation < 10 metres × *Precipitation* > 1000 mm		-0.035	-0.030				-0.083	-0.076
		(0.075)	(0.049)				(0.154)	(0.120)
Precipitation > 1000 mm		-0.063	-0.021				-0.113	-0.086
		(0.079)	(0.054)				(0.162)	(0.117)
ln (VIIRS radiance)				0.288***	0.285***			
				(0.008)	(0.009)			
F-test for $\hat{\lambda} = 1$				7784***	6085***			
Country fixed effects	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
City fixed effects	No	No	Yes	No	No	No	No	Yes
River & coast fixed effects	No	No	Yes	No	No	No	No	Yes
R-squared	0.098	0.098	0.440	0.590	0.627	0.079	0.079	0.367

Note: All regressions use a sample of N=3,637,696 points, which cover all parts of N=34,545 urban areas. The coordinates for the grid points, the elevation and precipitation indicators and the fixed effects are from the replication files of Kocornik-Mina et al (2020). The sources for the two sets of night-lights data are described in footnote 11 in our main text. Robust standard errors clustered at country level in ( ), ***p<0.01, ** p<0.05, * p<0.10.

3.1 Evidence on the DMSP Measurement Errors

With two sets of night-lights data on the same points in the same year we can examine the nature of the measurement error in the DMSP data, treating the VIIRS data as being more accurate.[12] We can also examine implications of these errors, to explain (in advance) why the VIIRS data show that economic activity is far more heavily concentrated in low-lying areas than what the DMSP data show. Consider a model: $y = \alpha + \beta x + u$, for an outcome variable y, an independent variable x, response coefficient β, and a pure random error, u. The outcome variable has an observed value y^* that is related to the true value by:

$$y^* = \theta + \lambda y + v \tag{1}$$

The textbook case of classical measurement error makes the assumptions that $\theta = 0, \lambda = 1$ and $E(v) = cov(y, v) = cov(x, v) = cov(u, v) = 0$, so that just white noise is added to the true value. Yet evidence from various branches of economics (Abay et al (2019) compile some estimates) is that errors are mean-reverting, $0 < \lambda < 1$. In that case, the estimator of the response coefficient if the error-ridden dependent variable is used is:

$$\beta_{y^*x} = \frac{cov(y^*,x)}{var(x)} = \frac{cov(\lambda\alpha+\lambda\beta x+\lambda u-v,x)}{var(x)} = \lambda\beta \tag{2}$$

In other words, with mean reverting errors in the (log) DMSP data, the estimate in column (1) of Table 2, showing how much greater is luminosity in low-lying areas relative to the national means, will be attenuated in proportion to the estimated mean-reversion parameter $\hat{\lambda}$.

Although we do not need the result until Section 4, it is also convenient to show here the consequences if the DMSP data are the RHS variable. Let the setup for the error-ridden RHS variable be as in equation (1) and assume that the outcome variable is measured without error. It can be shown (e.g. Gibson et al, 2015) that the response estimator becomes:

$$\beta_{yx^*} = \frac{cov(y,x^*)}{var(x^*)} = \beta\frac{\lambda\sigma_x^2}{\lambda^2\sigma_x^2+\sigma_v^2} \tag{3}$$

For the special case of classical measurement error, with $\lambda = 1$, equation (3) simply gives the usual result, of attenuation of the estimated coefficient in proportion to the reliability ratio of the mis-measured RHS variable. Yet with sufficiently strong mean reversion, the smaller first term in the denominator due to multiplying by λ^2 (for $0<\lambda<1$) may outweigh effects of adding variance of the random noise term (σ_v^2), making the denominator smaller than the numerator, and the regression coefficient β_{yx^*} in equation (3) is exaggerated not attenuated.

In columns (4) and (5) of Table 2 we report estimates of equation (1), with pixel-level log DMSP data regressed on log VIIRS values. In order to estimate the regressions we use the inverse-hyperbolic sine transformation, because 18.3% of pixels that appear lit according to DMSP have zero radiance with VIIRS data. Just as in Figure 2, with Washington DC lights

[12] Support for the assumption that the VIIRS data can be used as the truer value comes from Vuong (1989) tests that show that models using VIIRS data to predict local economic activity provide results that are closer to the truth than are models using DMSP data (Gibson, 2021; Zhang & Gibson, 2022).

spreading over unlit countryside of northern Virginia and Maryland according to the DMSP data, so too does this global sample of cities have unlit pixels where DMSP data suggest they are brightly lit (the pixels with zero radiance in VIIRS have DN values ranging from 0-63, with mean 12). The estimate of $\hat{\lambda} = 0.29$ is not sensitive to inclusion of country fixed effects, and if we add city fixed effects the mean reversion is even stronger, with $\hat{\lambda} = 0.24$. If we only use pixels with non-zero radiance, the mean reversion is hardly changed, with $\hat{\lambda} = 0.31$. In all cases the restriction needed for classical measurement error, that $\hat{\lambda} = 1$ is soundly rejected.[13]

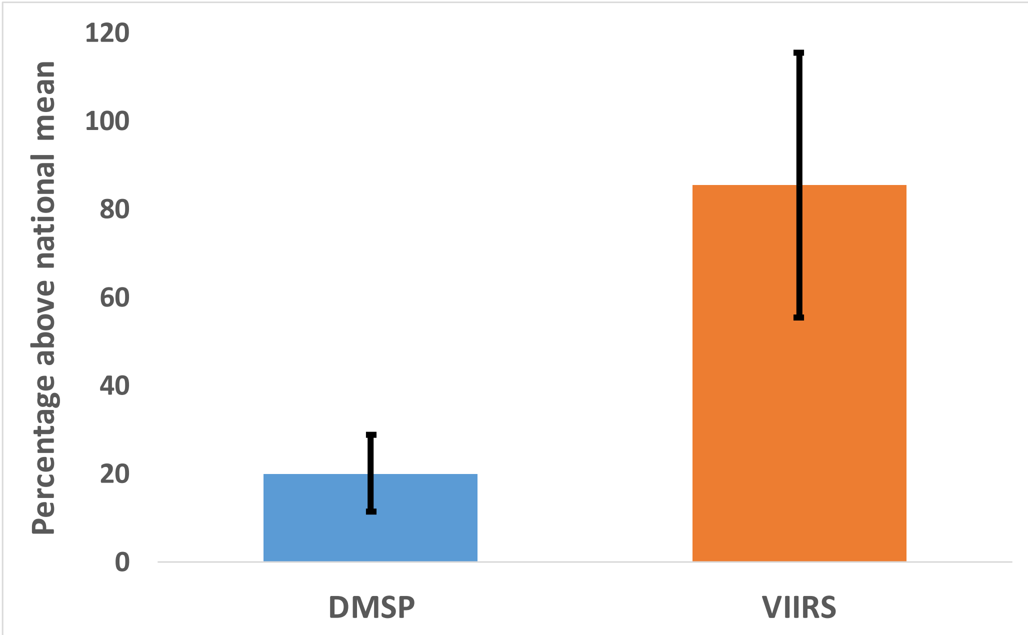
3.2 Impacts of the Mean-Reverting Measurement Error

From equation (2) we expect a regression coefficient to be attenuated to 0.29 of the actual value if error-ridden DMSP data are the LHS variable. So using more accurate VIIRS data should reveal an impact on luminosity of being low elevation approximately 3.5 times larger $\left(= 1/\hat{\lambda}\right)$ than what was shown in column (1). Indeed, the estimate in column (6) from VIIRS data shows this; the coefficient for low-lying pixels is 0.62. Allowing an interaction with the indicator for experiencing high precipitation events does not alter this effect. When city-level fixed effects are introduced in column (8) the coefficient on the low-lying indicator is 0.32, which is more than 5-times as high as what is estimated with DMSP data.

The percentage by which luminosity of low-lying pixels exceeds national means is shown in Figure 4, from the column (1) results with DMSP data and the column (6) results with VIIRS data. These percentage difference estimates and 95% confidence intervals use the approximate unbiased variances estimator of van Garderen and Shah (2002). According to DMSP data, low-lying pixels have luminosity that is 20% above the national mean (with a standard error of 4.4%). Yet the actual figure, based on the more accurate VIIRS data, is that radiance from low-lying pixels is 85% above the national mean (standard error of 15.3%). Evidently, the results in Kocornik-Mina et al (2020) greatly understate the potential economic risks from floods, which they argue are especially experienced by developing countries. It is also likely that their panel analysis of flood impacts for 2003-08 is biased by mean-reverting errors in DMSP data; these errors reflect fundamental aspects of DMSP sensors and data management, so there is no reason to believe that the errors we find in 2012 were atypical.

[13] The strength of mean-reversion is also sufficient for regression coefficients to be exaggerated when the lights data are on the RHS. The coefficient of variation (CoV) for (log) DMSP is 0.189, which is far smaller than the 0.613 for (log) VIIRS. If errors are random the variance of the mis-measured variable is larger than the variance of the more accurate variable, giving a 'reliability ratio' less than one (the variance of the mis-measured variable is the denominator). In the current case the 'shrinkage' of the denominator from the mean-reverting error makes it smaller than the numerator, which is the equation (3) condition for regression coefficients to be exaggerated.

Figure 4: Percentage Difference in Luminosity Between Low Elevation Urban Pixels and National Means (Error Bars Show 95% CI)



IV. Night Lights and Child Anthropometrics in Nigeria

The next paper we test to see if research findings change when the more accurate VIIRS night lights data are used in place of the inaccurate, coarse resolution, DMSP data is Amare et al (2020). This paper uses pixel-level DMSP values for reported latitude and longitude (lat-lon) coordinates of each enumeration area in the Demographic and Health Survey (DHS) for Nigeria.[14] Helpfully for our purposes, results are presented for 2013 (along with 2008); a year with both DMSP and VIIRS data available.[15] Before comparing results using the two data sources, we briefly highlight conclusions from Amare et al (2020) to provide salience to the comparisons. They report a strong positive association between urbanization (as proxied by DMSP night lights) and child nutritional outcomes (as proxied by anthropometrics). For

[14] To anonymize surveyed communities, DHS randomly displace reported coordinates up to 2km for urban areas and 5km for rural areas although this is not discussed in Amare et al (2020). With DMSP inherently blurred this may matter less than for precisely geo-referenced data. For example, we regress height-for-age z-scores of urban children on either log lights for DMSP pixels at the reported coordinates (and on 13 control variables described below) or on averages over all pixels in a 2km buffer around that point; coefficients were very similar: −0.055 (SE=0.042) for point data and −0.047 (SE=0.039) for buffer data. However, given lack of blurring of VIIRS data, we do account for the random displacement of DHS coordinates when linking VIIRS to the DHS data.

[15] We form annual estimates for 2013 from VIIRS monthly composites, using masking (Gibson, 2021) to reduce effects of outliers from ephemeral lights. Similar masking is used by Gibson et al (2021) and Roberts (2021). We do not use the same VIIRS data from Section III, because near-nadir annual composites used for the flooded city analysis are based on just one quarter of the available nights (observation angles are not near-nadir on other nights). Gaining spatial precision (but losing temporal coverage) is worthwhile for urban areas (in Section III), which should be lit continuously throughout the year. In contrast, the DHS locations in Nigeria cover far less brightly lit areas, and 65% of DHS clusters would appear unlit if using the near-nadir annual composite from Section III, even though the monthly all-angles data show that far fewer of the clusters are continuously unlit.

example, the average derivative between height-for-age *z*-scores (HAZ) and log lights is 0.31, using non-parametric regressions, and it is 0.04 for weight-for-height *z*-scores (WHZ). With the same outcome measures and controls, but with VIIRS night lights data rather than DMSP, we estimate the corresponding non-parametric average derivatives as zero and -0.06.

Amare et al (2020) also claim DMSP data are better than traditional urban indicators from census data, as outcomes can be studied along an urbanization continuum. In fact, as Section II shows, DMSP data are so blurred that one cannot see clearly where urban turns into rural. Also, DMSP data are so coarse, especially at the lower end of the distribution, they are effectively bottom-coded. For example, one-third of children in the 2013 DHS live in places DMSP records zero light yet VIIRS shows as lit.[16] In spite of these data problems, Amare et al (2020) argue that because the association they find weakens at brighter levels of lights, a policy of pursuing moderate population agglomeration is supported (relatedly, see Christiaensen and Kanbur (2017) and Gibson et al (2017) for arguments promoting secondary towns versus big cities). A key claim of Amare et al (p.64) is that: "[N]ightlight is found to significantly [and positively] predict child nutritional outcomes even after controlling for covariates known to influence child nutrition." Seemingly, not only do families in urbanized areas have attributes such as more education that help improve child nutrition, there is also an effect of urbanization *per se* that policy makers could exploit.

4.1 Evidence from Local Regression Plots

We start with nonparametric local polynomial regression plots relating log night lights to four anthropometric indicators—height-for-age *z* score (HAZ), stunted (HAZ < -2), weight-for-height *z* score (WHZ), and weight-for-age *z* score (WAZ). We use the full sample of 888 DHS clusters in 2013 (from which 23,220 children have full data). The charts in the top row of Figure 5 use DMSP data (log DN for the pixel at the reported lat-lon coordinate of the DHS cluster). The first two charts, for HAZ and stunting, match charts (e) and (f) of Figure 2 of Amare et al (2020), while the last two charts with DMSP data match (b) and (d) of their Figure 3 (titles of (c) and (d) in their paper seem to have switched). Unlike the charts in Amare et al (2020) we add vertical lines to show the boundaries for (sample-weighted) quartiles of children, ranked from having the lowest night light values to the highest. This addition matters because with DMSP data 57% of the children live in a DHS cluster whose DN value is zero so the charts for 2013 in Amare et al (2020) cover under one-half of the range of lighting conditions Nigerian children experience.[17] Their phrases like "intermediate level of urbanization" or "middle of the range" (p.69) may thus mislead because only the upper part of the full distribution was shown. The fan-shaped confidence intervals with a sharp kink in the middle of the third quartile reflects the sparsity of less-lit observations.

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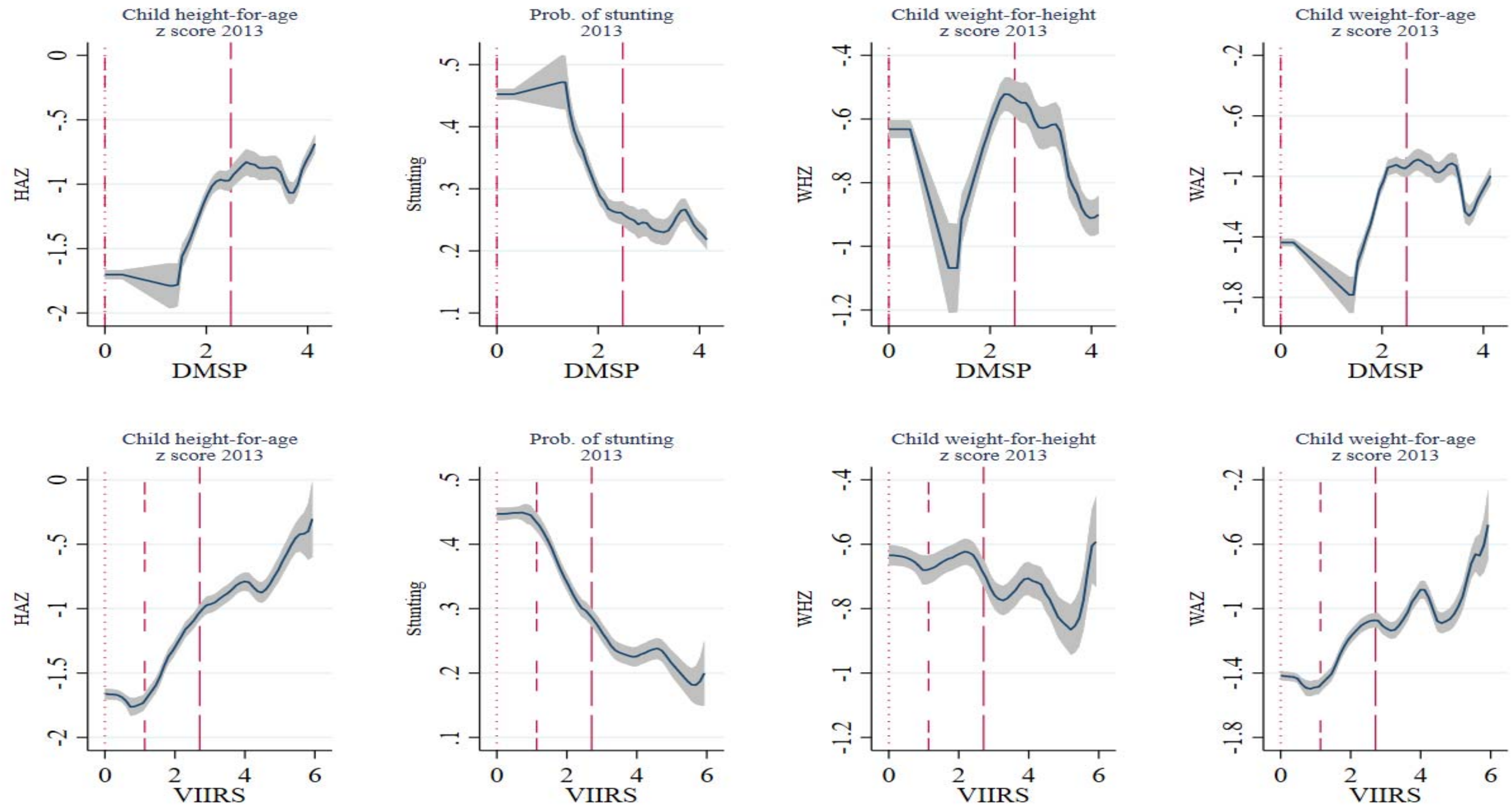
[16] Likewise, Chen and Nordhaus (2015) study 1°×1° grid cells over Africa, populated with 10,000 to 100,000 people and all illuminated according to VIIRS. Over one-half have zero light in DMSP data. The crudeness of DMSP sensors is shown by the type of lights researchers needed, to temporarily light previously dark area in a study of spatial accuracy for DMSP (Tuttle et al, 2013, 2014). They needed a bank of 1000-watt high pressure sodium lamps (each weighs about 25 kg) which are not the type of lights found in rural villages in Africa.

[17] To help interpret the quartile boundaries, the brightness of a secondary town like Wak in Figure 3 puts it in the middle of the second quartile of Figure 5, for lights measured with VIIRS.

Figure 5: Local Polynomial Regression Plots of Association Between Local Night Lights and Anthropometric Indicators for Nigerian Children



Notes: The x-axis for each chart is for the log of lights (DMSP is just a Digital Number while VIIRS measures radiance in nanoWatt/cm^2/sr) and the y-axis is for the anthropometric indicator. The non-parametric regressions are based on an Epanechnikov kernel function using a rule-of-thumb (ROT) bandwidth estimator. The vertical lines denote the boundaries between quartiles of (sample-weighted) children, ranked from those with least night lights through to those with most: dots for end of the first quartile; short dash for end of the second quartile; long dash for end of third quartile. Using DMSP more than 50 percent of children seem to live in a DHS cluster with lights equal to zero so dots and short dash overlaps

The bottom row of Figure 5 uses log VIIRS annual estimates for 2013. The superior low light detection capability of VIIRS shows just over three-quarters of Nigerian children live in lit areas, so the inter-quartile boundaries are clearly demarcated (with DMSP the 25th and 50th percentile indicators overlap). The VIIRS data show no anthropometric improvement for children below the 50th percentile, as lights get brighter—counter to the idea of a positive association between night lights and nutritional outcomes. For the one-half of children in the most luminous areas nutritional outcomes are better with more light—the average HAZ rises from −1.7 to −0.3 and the odds of being stunted fall from 44% to below 20%. Note however that this unconditional effect either reverses or disappears once covariates are added.

4.2 Evidence from Piecewise Regressions

Table 3 has regression counterparts to Figure 5 for HAZ. The other anthropometric indicators also respond differently to VIIRS to than DMSP but we focus on HAZ as the best long-run indicator. We use piecewise regressions to let relationships change between each quartile of children and to allow control variables to be included. We use the same controls as Amare et al (2020): the child's gender, age, and birth order, the mother's education and her age at first birth, education of the mother's partner, family wealth quintile, and indicators for having a TV, for reading newspapers and for visiting family planning agents.

When the VIIRS data are used, for regressions reported in the last three columns of Table 3, there is a negative relationship between night lights and HAZ for Quartile 2, and positive ones for the top two quartiles.[18] The negative effect for Quartile 2 is slightly muted if controls are added (Table 3, Panel B) while the relationships for Quartiles 3 and 4 become statistically insignificant. A quadratic specification in log-lights is introduced in Panel C, to allow for further non-linearity; there is little to favour this over the linear specification, with only Quartile 4 having statistically significant terms (with a turning point at the log-lights level of the 89th percentile child; below that point the relationship between night lights and HAZ is negative, controlling for covariates). Thus, VIIRS data generally do not support the Amare et al (2020) claim of child nutritional outcomes being positively associated with night lights.

The DMSP data yield no piecewise results for the first two quartiles because 57% of Nigerian children in 2013 are in areas with no lights sensed by DMSP. For Quartiles 3 and 4, statistically insignificant coefficients are estimated when no control variables are used, with a negative and statistically significant coefficient for Quartile 3 with controls included. The quadratic specification of log-lights in Panel C is statistically significant for Quartile 4, with a turning point at the log-lights level of the 86th percentile child (lights negatively relate to HAZ prior to that point). Thus, just the top 14% of children (in terms of having the most DMSP light) have height-for-age *z* scores positively (and statistically significantly) related to night lights (conditional on covariates), in contrast to results reported in Amare et al (2020).

[18] Quartile 1 has just 17 children with non-zero lights, all from the same DHS cluster with recorded radiance of 0.82 nW/cm^2/sr. This is too few for meaningful estimates so we do not report any results for Quartile 1. If we combine observations from that cluster with those in Quartile 2, results are largely unchanged; for example, the coefficient for the linear piecewise with controls goes from −0.331 in Table 3 to −0.322.

Table 3: Piecewise Regressions Relating Height-for-age *z*-scores of Nigerian Children (aged 5 and under) to Night Lights, by Quartile

	DMSP 2013 Annual Composite				VIIRS 2013 Annual Estimate (from masked monthly data)			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Quartile 1	Quartile 2	Quartile 3	Quartile 4
			Panel A: Linear Piecewise Without Controls					
ln (night lights)			0.0011	0.1051		-0.3986***	0.4031***	0.1357*
			(0.0517)	(0.1137)		(0.1456)	(0.1529)	(0.0800)
Intercept			-1.1486***	-1.2176***		-1.4836***	-2.1067***	-1.3457***
			(0.0825)	(0.3981)		(0.0856)	(0.3228)	(0.3192)
Child and parent controls			No	No		No	No	No
R-squared			0.0000	0.0008		0.0081	0.0088	0.0030
			Panel B: Linear Piecewise With Controls					
ln (night lights)			-0.1165**	-0.0739		-0.3308***	0.1705	0.0320
			(0.0500)	(0.0882)		(0.1142)	(0.1049)	(0.0601)
Intercept			-1.7260***	-2.0876***		-1.9075***	-2.5439***	-2.4172***
			(0.2805)	(0.4433)		(0.2501)	(0.3001)	(0.3930)
Child and parent controls			Yes	Yes		Yes	Yes	Yes
R-squared			0.1116	0.0904		0.1358	0.1445	0.0899
			Panel C: Quadratic Piecewise With Controls					
ln (night lights)			-0.3376	-3.2709**		-0.0261	-0.0265	-0.9665*
			(0.2561)	(1.4830)		(0.5206)	(0.9327)	(0.5727)
[ln (night lights)]^2			0.1026	0.4656**		-0.3052	0.0512	0.1228*
			(0.1210)	(0.2144)		(0.4965)	(0.2384)	(0.0682)
Intercept			-1.6666***	3.3587		-1.9210***	-2.3659***	-0.4776
			(0.2763)	(2.5378)		(0.2527)	(0.8824)	(1.1639)
Child and parent controls			Yes	Yes		Yes	Yes	Yes
R-squared			0.1121	0.0931		0.1361	0.1446	0.0913
Observations (weighted)	5805.4	5805.2	5805.8	5803.9	5806.2	5806.5	5802.7	5804.8

Note: The child and parent controls are child gender, age, and birth order, mother's education, mother's age at first birth, father's education, wealth quintile, and indicators for household having a TV, for reading newspapers and for visiting family planning agents. There are no results for the first two quartiles with DMSP, and for the first quartile with VIIRS, as recorded lights are zero for the DHS clusters of children in those quartiles. Cluster robust standard errors in ( ), ***p<0.01, ** p<0.05, * p<0.10.

4.3 Evidence from Polynomial Specifications

Table 3 cannot be directly compared to Amare et al (2020) because rather than using piecewise regressions for non-linearity they used a fourth order polynomial, with centered log-lights and squared, cubic, and quartic terms. This was to allow "sufficient nonlinearities in the estimations" (p.69) although no test of this specification was reported. The quartic results (in their Table 2) used pooled 2008 and 2013 data so we cannot use VIIRS to replicate as VIIRS started after 2008.[19] Instead, marginal effects from a similar specification on 2013 DMSP and VIIRS cross-sectional data are reported in Table 4. Unlike Amare et al (2020) we show results for six different polynomial specifications, ranging from linear through to sextic, so the quartic specification that is their exclusive focus can be put into context. The regression results that underlie these marginal effects are reported in Appendix Tables 1a to 4b.

The marginal partial effects are calculated for each observation and then averaged so that effects of multiple coefficients in polynomial specifications be captured in a single value. A clear takeaway from the table, which is contrary to discussion in Amare et al (2020) but does not illuminate the DMSP versus VIIRS issue, is that children in areas with more lights, *ceteris paribus*, seem to have worse nutritional outcomes: lower HAZ, WHZ and WAZ and a higher stunting risk.[20] The estimates are more precise with VIIRS data; the limited range of the DMSP data, with 57% of children living in clusters with the same DN value (zero), naturally limits precision of parameters estimated from DMSP data.[21]

The marginal effects in Table 4 appear far larger if DMSP data are used. For a quartic polynomial (the specification of Amare et al (2020)) we find marginal effects are six-times as high, on average, using DMSP rather than VIIRS. For a linear specification, marginal effects with DMSP are approximately twice what VIIRS shows. These differences are in line with the equation (3) result; strong mean-reversion in a right-hand side variable exaggerates regression coefficients rather than attenuates them as occurs under classical measurement error. Thus the DMPS data seemingly give urbanization a more powerful association (albeit in the opposite direction to what Amare et al (2020) report) with child anthropometrics than is implied by the less error-ridden VIIRS data, particularly in specifications with higher order polynomials.

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[19] Amare et al (2020, p.66) report a 23% higher average DN value in 2013 than in 2008 for their sample. This rise likely helps identification in their pooled specification but may not be from actual changes in luminosity. The F18 satellite providing the 2013 data always reports higher DN values than does F16 providing the 2008 data. For example, the DN jumped by 32% when F16 was replaced the next year by F18, for a region where lighting should have been stable over time (Gibson et al, 2020). Likewise, Tuttle et al (2004) show significantly higher values from F18 than F16 when reporting on the same light source on the same nights. The inconsistency in DN values between satellites reflects the lack of calibration of the DMSP sensors.

[20] Appendix A discusses our inability to reproduce the results reported by Amare et al (2020). We append this discussion as the issues raised are tangential to our main purpose of comparing findings using VIIRS data versus using DMSP. Tables 1-3 in the Appendix report results using the full DHS samples for 2008 and 2013 in pooled specifications with DMSP data using the same controls as Amare et al (2020). The appendix results are similar to the cross-sectional results for 2013 that we report in Table 4. In particular, average (partial) marginal effects of DMSP night lights on HAZ, WHZ and WAZ are negative, contrary to what Amare et al (2020) report.

[21] This also shows up with multicollinearity diagnostics. The condition number for the quartic model is 200 with DMSP but only 49 with VIIRS. Belsey et al (1980) suggest that coefficient estimates can have substantial errors when condition numbers are above 100.

Table 4: Marginal Effects of Log Lights on Anthropometric Indicators for Nigerian Children: Varying the Polynomial Specification and Lights Data

	DMSP 2013 Annual Composite				VIIRS 2013 Annual Estimate (from masked monthly data)			
Polynomial specification	HAZ	Stunted	WHZ	WAZ	HAZ	Stunted	WHZ	WAZ
Linear (1 term)	-0.008	-0.001	-0.127	-0.092	-0.003	0.000	-0.087	-0.061
	(0.024)	(0.005)	(0.029)	(0.024)	(0.022)	(0.005)	(0.024)	(0.021)
Quadratic (2 terms)	-0.003	-0.004	-0.092	-0.064	-0.035	0.004	-0.083	-0.077
	(0.030)	(0.007)	(0.029)	(0.027)	(0.026)	(0.006)	(0.025)	(0.023)
Cubic (3 terms)	0.092	-0.012	-0.386	-0.202	-0.084	0.018	-0.058	-0.085
	(0.130)	(0.030)	(0.146)	(0.136)	(0.047)	(0.011)	(0.043)	(0.040)
Quartic (4 terms)	-1.033	0.142	-1.081	-1.265	-0.232	0.041	-0.112	-0.207
	(0.505)	(0.121)	(0.523)	(0.518)	(0.080)	(0.019)	(0.074)	(0.065)
Quintic (5 terms)	1.744	-0.169	-3.536	-1.497	-0.248	0.051	-0.103	-0.213
	(2.269)	(0.504)	(2.380)	(2.419)	(0.135)	(0.033)	(0.121)	(0.109)
Sextic (6 terms)	-10.500	3.090	-6.154	-11.250	-0.019	-0.001	-0.268	-0.211
	(9.133)	(2.060)	(7.588)	(8.200)	(0.243)	(0.059)	(0.200)	(0.200)

Note: HAZ is the height-for-age z-score, stunted is an indicator for HAZ<–2, WHZ is the weight-for-height z-score and WAZ is the weight-for-age z-score. Each row of the table reports the average marginal (partial) effect (dy/dx) of log lights coming from a separate regression of the anthropometric indicator on centered log lights, and polynomials of centered log lights up to the sixth order, along with controls for child gender, age, and birth order, mother's education, mother's age at first birth, father's education, wealth quintile, and indicators for household having a TV, for reading newspapers and for visiting family planning agents. There are 48 regressions in total, whose full results are reported in Appendix Tables 1a to 4b. Cluster robust standard errors in ( ), ***p<0.01, ** p<0.05, * p<0.10.

Table 5: Non-parametric Regressions of Child Anthropometric Indicators on Night Lights: Nigeria 2013

	HAZ		WHZ		WAZ		Stunting		Wasting	
	VIIRS	DMSP	VIIRS	DMSP	VIIRS	DMSP	VIIRS	DMSP	VIIRS	DMSP
Average predictive mean	-1.2854***	-1.2955***	-0.5857***	-0.5980***	-1.1701***	-1.1840***	0.3539***	0.3557***	0.1658***	0.1687***
	(0.0142)	(0.0164)	(0.0109)	(0.0106)	(0.0096)	(0.0099)	(0.0035)	(0.0040)	(0.0031)	(0.0027)
Centred ln(lights): Average derivative	0.0004	0.0034	-0.0639***	-0.0973***	-0.0425***	-0.0657***	0.0005	-0.0014	0.0137***	0.0204***
	(0.0106)	(0.0130)	(0.0089)	(0.0089)	(0.0080)	(0.0089)	(0.0026)	(0.0029)	(0.0023)	(0.0024)
Child and parental characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,041	23,012	23,041	23,012	23,041	23,012	23,041	23,012	23,041	23,012
R-squared	0.3861	0.3807	0.3005	0.2949	0.3505	0.3462	0.3560	0.3543	0.2952	0.2899

Note: HAZ is height-for-age z-score, stunted is an indicator for HAZ<–2, WHZ is weight-for-height z-score, wasting is an indicator for WHZ<–2, and WAZ is weight-for-age z-score. Each column of the table reports the average predictive mean and the (average derivative) marginal effect of log lights on the anthropometric indicator coming from a separate non-parametric regression that also includes controls for child gender, age, and birth order, mother's education, mother's age at first birth, father's education, wealth quintile, and indicators for household having a TV, for reading newspapers and for visiting family planning agents. The non-parametric regressions are estimated using an Epanechnikov kernel function employing a rule-of-thumb (ROT) bandwidth estimator. Bootstrap standard errors in ( ), ***p<0.01, ** p<0.05, * p<0.10.

4.4 Non-parametric Regressions

The marginal effects in Table 4 are from parametric specifications and even though a consistent pattern shows up across all the polynomials, non-parametrics provide another way to assess the robustness of the findings. A further reason for reporting nonparametric results is that Amare et al (2020) present these, separately for 2013 in their Table 3, allowing a direct comparison with our results. Table 5 reports non-parametric average predictive means and marginal effects of lights (average derivatives)—matching what Amare et al (2020) report. While average predictive means are similar to what Amare et al report the average derivatives are not. Specifically, we find lights have significant negative effects on WHZ and WAZ. Relatedly, wasting (WHZ < -2) is significantly higher, *ceteris paribus*. The magnitude of these effects is about 50% higher when using the DMSP data than when using the VIIRS data, which is again consistent with impacts of strongly mean-reverting measurement errors in a right-hand side variable exaggerating results when DMSP data are used.

4.5 Using Dichotomous Indicators for Urban Areas

To study Amare et al's (2020) claim that night lights data are better than traditional urban/rural indicators from census data we used four different dichotomous indicators of urban/rural status: a census indicator for each DHS cluster, a dummy for DMSP exceeding zero for the pixel mapping to the DHS cluster coordinates, a dummy if any DN in a 2 km buffer around DHS cluster coordinates is positive, and a dummy if VIIRS records any positive radiance values in that 2 km buffer. In regressions without control variables, the DHS census indicator suggests urban children are 0.70 *z*-scores taller, on average, than are rural children. The two DMSP-derived urban indicators give similar gaps, of 0.71 and 0.74, while the VIIRS-based indicator gives a gap of 0.64. Once control variables are included the statistical significance of these gaps all disappear (coefficients range from -0.01 to 0.06, with standard errors always exceeding the coefficient). Similarity of results across the four ways of measuring urbanity suggests no special insight is gained from using satellite-detected night lights rather than using traditional urban/rural indicators based on census classifications.

V. Conclusions

Economists in the last decade have published many articles using night lights data, especially for research on developing countries where conventional sub-national economic data are less available or less accurate due to limited statistical capacity and to the predominant economic activities. Most of these articles use DMSP data, which have spatially mean-reverting errors that may bias estimation results, irrespective of whether lights data are on the left-hand side or right-hand side of regression equations. Far more accurate VIIRS night lights data have been available for a decade but have been largely ignored by economists.

Likewise, economists have largely ignored remote sensing studies that discuss sources of error in DMSP data and that show spatial resolution of DMSP sensors is far coarser than the 30 arc-second (roughly 1 km^2) output grid. Amongst 631 references in the applied papers covered in Table 1 (so not the Goldblatt et al (2020) methodological/validation study) there are just 12 to the remote sensing literature. Three of the papers in Table 1 cite no remote sensing studies at all. Remote sensing practitioners have a comparative advantage in using satellite-detected night lights data so ignoring their insights likely impairs the quality of analyses. In particular, economic studies using pixel-level DMSP data seem misguided once it is understood that the DMSP data do not detect differences in night lights for areas as small as 1 km^2. Simply looking at the data, along the lines of Figures 2 and 3, should have raised doubts about the wisdom of pixel-level analyses.

In this paper we examined how recent published findings based on pixel-level DMSP data change when more accurate VIIRS night lights data are used. Our first example finds urban economic activity is far more concentrated in low-lying and flood-prone areas than is found by a recent paper using DMSP data. We find over a four-fold difference in results from using VIIRS compared with using DMSP data. In our second example we show that urbanization, as proxied by night lights, is not *ceteris paribus* associated with better child nutritional outcomes in Nigeria, contrary to what is claimed in a recent paper. In this case the DMSP data were on the right-hand side of regression equations and the spatially mean-reverting errors cause exaggeration of estimated effects. In contrast, the flooded cities example had night lights data on the left-hand side, where the mean-reverting errors cause attenuation bias in the estimated treatment effects. Given that we have used examples with DMSP data on either side of regression equations, the generality of the biases that we show suggest that there will be many studies in the economics literature whose conclusions may have been affected by relying on noisy DMSP night lights data.

Our two examples cover critical issues facing poor people: vulnerability to natural disasters like flooding and determinants of inadequate growth of children that can lead to substantially stunted lives. The noisy DMSP night lights data distort conclusions drawn from these analyses and could lead to inappropriate policy interventions, especially given the paucity of other sources of data to aid contestability of policy advice in developing countries. It is an open question as to how many other published papers that may have influenced policy in developing countries need re-examination to see if the patterns they report also change when using the more accurate and precise VIIRS data.

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Appendix Table 1a: Results for Various Polynomial Specifications Relating HAZ to DMSP Night Lights, Nigeria, 2013

	Specification of the Polynomial for the Centered Value of the Logarithm of DMSP Night Lights					
	Linear	Quadratic	Cubic	Quartic	Quintic	Sextic
Terms in the Polynomial	(1)	(2)	(3)	(4)	(5)	(6)
ln (lights) – centred	-0.0079	-0.0015	-0.0345	0.6153**	-0.5372	3.1122
	(0.0241)	(0.0323)	(0.0514)	(0.2829)	(0.9613)	(2.7837)
ln (lights) – centred-square		-0.0056	-0.0537	0.1648	0.4828*	-2.4133
		(0.0165)	(0.0672)	(0.1162)	(0.2649)	(2.1116)
ln (lights) – centred-cubic			0.0189	-0.3947**	0.2873	-0.8698
			(0.0248)	(0.1792)	(0.5742)	(0.9861)
ln (lights) – centred-quartic				0.0976**	-0.363	1.9851
				(0.0414)	(0.3656)	(1.7346)
ln (lights) – centred-quintic					0.0787	-0.8923
					(0.0617)	(0.7130)
ln (lights) – centred-sextic						0.1281
						(0.0946)
Child and parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.8785***	-1.8651***	-1.7998***	-2.2337***	-1.7509***	-2.8433***
	(0.1372)	(0.1420)	(0.1662)	(0.2504)	(0.4646)	(0.9212)
F-test for all lights terms=0	0.106	0.126	0.264	1.62	1.66	1.611
p-value for *F*-test on all lights terms	0.745	0.881	0.851	0.167	0.142	0.141
Condition number (multicollinearity)	21.6	22.8	36.5	200.1	1142.0	7246.0
Bayesian Information Criteria	95117	95126	95134	95121	95124	95126

Notes: HAZ is height-for-age *z* score. Control variables are the same as listed in Table 3. N=23,123. Cluster-robust standard errors in ( ), ***p<0.01, ** p<0.05, * p<0.10. The specification in column (4) matches the one used by Amare et al (2020).

Appendix Table 1b: Results for Various Polynomial Specifications Relating HAZ to VIIRS Night Lights, Nigeria, 2013

	Specification of the Polynomial for the Centered Value of the Logarithm of VIIRS Night Lights					
	Linear	Quadratic	Cubic	Quartic	Quintic	Sextic
Terms in the Polynomial	(1)	(2)	(3)	(4)	(5)	(6)
ln (lights) – centred	-0.003	-0.04	-0.0069	0.1635**	0.1714*	0.1778*
	(0.0221)	(0.0272)	(0.0328)	(0.0710)	(0.0938)	(0.0922)
ln (lights) – centred-square		0.0275**	0.0563**	0.0520**	0.0425	0.1914
		(0.0112)	(0.0268)	(0.0261)	(0.0659)	(0.1453)
ln (lights) – centred-cubic			-0.0107	-0.0788***	-0.0816**	-0.1378***
			(0.0078)	(0.0273)	(0.0352)	(0.0497)
ln (lights) – centred-quartic				0.0158***	0.0193	-0.0285
				(0.0056)	(0.0243)	(0.0489)
ln (lights) – centred-quintic					-0.0006	0.0264
					(0.0038)	(0.0217)
ln (lights) – centred-sextic						-0.0035
						(0.0026)
Child and parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.8721***	-1.9442***	-1.9872***	-2.0071***	-2.0042***	-2.0433***
	(0.1359)	(0.1359)	(0.1391)	(0.1386)	(0.1413)	(0.1479)
F-test for all lights terms=0	0.019	3.022	2.147	3.809	3.454	3.698
p-value for F-test on all lights terms	0.891	0.049	0.093	0.004	0.004	0.001
Condition number (multicollinearity)	21.54	22.43	23.22	49.19	151.6	491.4
Bayesian Information Criteria	95117	95102	95105	95085	95095	95098

Notes: HAZ is height-for-age z score. Control variables are the same as listed in Table 3. N=23,123. Cluster-robust standard errors in ( ), ***p<0.01, ** p<0.05, * p<0.10.

Appendix Table 2a: Results for Various Polynomial Specifications Relating Stunting to DMSP Night Lights, Nigeria, 2013

	Specification of the Polynomial for the Centered Value of the Logarithm of DMSP Night Lights					
	Linear	Quadratic	Cubic	Quartic	Quintic	Sextic
Terms in the Polynomial	(1)	(2)	(3)	(4)	(5)	(6)
ln (lights) – centred	-0.0012	-0.0052	-0.0024	-0.0914	0.0377	-0.9333
	(0.0054)	(0.0076)	(0.0118)	(0.0680)	(0.2165)	(0.6350)
ln (lights) – centred-square		0.0035	0.0075	-0.0224	-0.058	0.7126
		(0.0038)	(0.0160)	(0.0288)	(0.0561)	(0.4722)
ln (lights) – centred-cubic			-0.0016	0.0550	-0.0214	0.2865
			(0.0058)	(0.0428)	(0.1296)	(0.2313)
ln (lights) – centred-quartic				-0.0134	0.0382	-0.5866
				(0.0098)	(0.0799)	(0.3906)
ln (lights) – centred-quintic					-0.0088	0.2496
					(0.0133)	(0.1571)
ln (lights) – centred-sextic						-0.0341*
						(0.0205)
Child and parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.5508***	0.5425***	0.5370***	0.5964***	0.5423***	0.8330***
	(0.0310)	(0.0326)	(0.0383)	(0.0595)	(0.1071)	(0.2102)
F-test for all lights terms=0	0.052	0.422	0.282	0.680	0.679	1.202
p-value for *F*-test on all lights terms	0.820	0.656	0.838	0.606	0.639	0.303
Condition number (multicollinearity)	21.6	22.8	36.5	200.1	1142.0	7246.0
Bayesian Information Criteria	29498	29505	29515	29517	29526	29526

Notes: Stunted is an indicator variable for HAZ < -2. Control variables are the same as listed in Table 3. N=23,123. Cluster-robust standard errors in ( ), ***p<0.01, ** p<0.05, * p<0.10. The specification in column (4) matches the one used by Amare et al (2020).

Appendix Table 2b: Results for Various Polynomial Specifications Relating Stunting to VIIRS Night Lights, Nigeria, 2013

	Specification of the Polynomial for the Centered Value of the Logarithm of VIIRS Night Lights					
	Linear	Quadratic	Cubic	Quartic	Quintic	Sextic
Terms in the Polynomial	(1)	(2)	(3)	(4)	(5)	(6)
ln (lights) – centred	-0.0001	0.0043	-0.0054	-0.0321*	-0.0369	-0.0384*
	(0.0048)	(0.0059)	(0.0072)	(0.0171)	(0.0231)	(0.0227)
ln (lights) – centred-square		-0.0032	-0.0117*	-0.0110*	-0.0052	-0.0386
		(0.0024)	(0.0061)	(0.0060)	(0.0154)	(0.0348)
ln (lights) – centred-cubic			0.0031*	0.0138**	0.0155*	0.0281**
			(0.0018)	(0.0065)	(0.0086)	(0.0115)
ln (lights) – centred-quartic				-0.0025*	-0.0046	0.0061
				(0.0013)	(0.0058)	(0.0117)
ln (lights) – centred-quintic					0.0004	-0.0057
					(0.0009)	(0.0051)
ln (lights) – centred-sextic						0.0008
						(0.0006)
Child and parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.5523***	0.5608***	0.5734***	0.5765***	0.5748***	0.5836***
	(0.0305)	(0.0309)	(0.0320)	(0.0320)	(0.0324)	(0.0340)
F-test for all lights terms=0	0.000	0.879	1.216	1.461	1.184	1.297
p-value for F-test on all lights terms	0.987	0.416	0.303	0.212	0.315	0.256
Condition number (multicollinearity)	21.54	22.43	23.22	49.19	151.6	491.4
Bayesian Information Criteria	29498	29502	29502	29499	29509	29513

Notes: Stunted is an indicator variable for HAZ < -2. Control variables are the same as listed in Table 3. N=23,123. Cluster-robust standard errors in ( ), ***p<0.01, ** p<0.05, * p<0.10.

Appendix Table 3a: Results for Various Polynomial Specifications Relating WHZ to DMSP Night Lights, Nigeria, 2013

	Specification of the Polynomial for the Centered Value of the Logarithm of DMSP Night Lights					
	Linear	Quadratic	Cubic	Quartic	Quintic	Sextic
Terms in the Polynomial	(1)	(2)	(3)	(4)	(5)	(6)
ln (lights) – centred	-0.1271***	-0.0840***	0.0189	0.4202	1.4391	2.2192
	(0.0289)	(0.0306)	(0.0505)	(0.3012)	(0.9681)	(2.2449)
ln (lights) – centred-square		-0.0380*	0.1117	0.2466**	-0.0345	-0.6535
		(0.0214)	(0.0686)	(0.1083)	(0.3294)	(1.8529)
ln (lights) – centred-cubic			-0.0589**	-0.3143	-0.9172	-1.1645
			(0.0272)	(0.1943)	(0.5667)	(0.7320)
ln (lights) – centred-quartic				0.0603	0.4675	0.9693
				(0.0478)	(0.4003)	(1.4615)
ln (lights) – centred-quintic					-0.0696	-0.2771
					(0.0719)	(0.6391)
ln (lights) – centred-sextic						0.0274
						(0.0892)
Child and parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.3545***	-1.2639***	-1.4669***	-1.7349***	-2.1617***	-2.3952***
	(0.1051)	(0.1139)	(0.1483)	(0.2276)	(0.4333)	(0.6819)
F-test for all lights terms=0	19.280	10.260	7.181	6.307	5.996	5.200
p-value for F-test on all lights terms	0.001	0.001	0.001	0.001	0.001	0.001
Condition number (multicollinearity)	21.6	22.8	36.5	200.1	1142.0	7246.0
Bayesian Information Criteria	86279	86258	86238	86235	86237	86247

Notes: WHZ is weight-for-height z score. Control variables are the same as listed in Table 3. N=23,123. Cluster-robust standard errors in ( ), ***p<0.01, ** p<0.05, * p<0.10. The specification in column (4) matches the one used by Amare et al (2020).

Appendix Table 3b: Results for Various Polynomial Specifications Relating WHZ to VIIRS Night Lights, Nigeria, 2013

	Specification of the Polynomial for the Centered Value of the Logarithm of VIIRS Night Lights					
	Linear	Quadratic	Cubic	Quartic	Quintic	Sextic
Terms in the Polynomial	(1)	(2)	(3)	(4)	(5)	(6)
ln (lights) – centred	-0.0869***	-0.0829***	-0.1003***	-0.0382	-0.0425	-0.047
	(0.0237)	(0.0264)	(0.0378)	(0.0759)	(0.0823)	(0.0830)
ln (lights) – centred-square		-0.0030	-0.0182	-0.0197	-0.0146	-0.1219
		(0.0128)	(0.0246)	(0.0245)	(0.0798)	(0.1344)
ln (lights) – centred-cubic			0.0056	-0.0192	-0.0176	0.0229
			(0.0082)	(0.0270)	(0.0297)	(0.0508)
ln (lights) – centred-quartic				0.0057	0.0039	0.0382
				(0.0055)	(0.0263)	(0.0426)
ln (lights) – centred-quintic					0.0003	-0.0191
					(0.0045)	(0.0196)
ln (lights) – centred-sextic						0.0025
						(0.0024)
Child and parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.2976***	-1.2898***	-1.2671***	-1.2743***	-1.2759***	-1.2477***
	(0.1034)	(0.1074)	(0.1153)	(0.1157)	(0.1198)	(0.1253)
F-test for all lights terms=0	13.430	6.861	4.676	3.574	2.924	2.497
p-value for *F*-test on all lights terms	0.001	0.001	0.003	0.007	0.013	0.021
Condition number (multicollinearity)	21.54	22.43	23.22	49.19	151.6	491.4
Bayesian Information Criteria	86347	86357	86364	86368	86378	86383

Notes: WHZ is weight-for-height *z* score. Control variables are the same as listed in Table 3. *N*=23,123. Cluster-robust standard errors in ( ), ****p*<0.01, ** *p*<0.05, * *p*<0.10.

Appendix Table 4a: Results for Various Polynomial Specifications Relating WAZ to DMSP Night Lights, Nigeria, 2013

	Specification of the Polynomial for the Centered Value of the Logarithm of DMSP Night Lights					
	Linear	Quadratic	Cubic	Quartic	Quintic	Sextic
Terms in the Polynomial	(1)	(2)	(3)	(4)	(5)	(6)
ln (lights) – centred	-0.0915***	-0.0584**	-0.0102	0.6033**	0.7	3.6062
	(0.0244)	(0.0287)	(0.0511)	(0.2958)	(1.0006)	(2.4443)
ln (lights) – centred-square		-0.0291	0.041	0.2474**	0.2207	-2.0856
		(0.0183)	(0.0673)	(0.1108)	(0.3107)	(1.9553)
ln (lights) – centred-cubic			-0.0276	-0.4181**	-0.4753	-1.3967*
			(0.0260)	(0.1893)	(0.5913)	(0.8228)
ln (lights) – centred-quartic				0.0921**	0.1307	2.0007
				(0.0454)	(0.4000)	(1.5683)
ln (lights) – centred-quintic					-0.0066	-0.7799
					(0.0701)	(0.6740)
ln (lights) – centred-sextic						0.102
						(0.0928)
Child and parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-2.0936***	-2.0241***	-2.1193***	-2.5289***	-2.5694***	-3.4393***
	(0.1011)	(0.1058)	(0.1413)	(0.2287)	(0.4596)	(0.7841)
F-test for all lights terms=0	14.010	7.725	5.273	4.994	4.201	3.670
p-value for *F*-test on all lights terms	0.001	0.001	0.001	0.001	0.001	0.001
Condition number (multicollinearity)	21.6	22.8	36.5	200.1	1142.0	7246.0
Bayesian Information Criteria	79651	79638	79639	79608	79618	79618

Notes: WAZ is weight-for-age *z* score. Control variables are the same as listed in Table 3. N=23,123. Cluster-robust standard errors in ( ), ***p<0.01, ** p<0.05, * p<0.10. The specification in column (4) matches the one used by Amare et al (2020).

Appendix Table 4b: Results for Various Polynomial Specifications Relating WAZ to VIIRS Night Lights, Nigeria, 2013

	Specification of the Polynomial for the Centered Value of the Logarithm of VIIRS Night Lights					
	Linear	Quadratic	Cubic	Quartic	Quintic	Sextic
Terms in the Polynomial	(1)	(2)	(3)	(4)	(5)	(6)
ln (lights) – centred	-0.0611***	-0.0792***	-0.0739**	0.0667	0.0697	0.0697
	(0.0207)	(0.0237)	(0.0340)	(0.0676)	(0.0747)	(0.0747)
ln (lights) – centred-square		0.0134	0.018	0.0145	0.0108	0.0118
		(0.0115)	(0.0226)	(0.0223)	(0.0732)	(0.1316)
ln (lights) – centred-cubic			-0.0017	-0.0578**	-0.0589**	-0.0593
			(0.0075)	(0.0239)	(0.0269)	(0.0466)
ln (lights) – centred-quartic				0.0130***	0.0143	0.0140
				(0.0050)	(0.0240)	(0.0423)
ln (lights) – centred-quintic					-0.0002	0.0000
					(0.0041)	(0.0194)
ln (lights) – centred-sextic						0.0000
						(0.0024)
Child and parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-2.0508***	-2.0861***	-2.0929***	-2.1092***	-2.1081***	-2.1084***
	(0.0982)	(0.0997)	(0.1029)	(0.1020)	(0.1071)	(0.1113)
F-test for all lights terms=0	8.698	5.757	3.882	4.704	3.722	3.162
p-value for *F*-test on all lights terms	0.003	0.003	0.009	0.001	0.002	0.004
Condition number (multicollinearity)	21.54	22.43	23.22	49.19	151.6	491.4
Bayesian Information Criteria	79701	79700	79709	79680	79690	79700

Notes: WAZ is weight-for-age z score. Control variables are the same as listed in Table 3. N=23,123. Cluster-robust standard errors in ( ), ***p<0.01, ** p<0.05, * p<0.10.

Appendix A

Issues With Reproducing Results from Amare et al (2020) Even Using Only DMSP Data

In contrast to the flooded cities analysis, we could not reproduce the results reported by Amare et al (2020), even just using DMSP data. This non-reproducibility is tangential to our main point about how using DMSP data instead of the more accurate and precise VIIRS data is likely to create an econometric bias that matters to policy in developing countries. We therefore confine the discussion to an appendix. We have two motivations for including this discussion: cases of non-reproducibility of published research are concerning, especially when the research relates to an important public policy issue (the drivers of child nutritional outcomes) in a setting where resource constraints make it likely that results published in high quality international journals go unchallenged and may be accepted uncritically as an input into policy. Second, other research teams may also seek to replicate the Amare et al (2020) results and so we owe it to these other researchers to document what we found during our attempts at this process.

The Amare et al (2020) results are ostensibly based on a sample of 560 DHS clusters where the reported lat-lon coordinates for the 2008 DHS cluster and the reported coordinates for the 2013 DHS cluster are within 10 km of each other. These authors considered this distance close enough that a cluster from the 2008 survey and a cluster from the 2013 survey could be assumed to come from the same community.[22] Based on this assumption, Amare et al (2020) introduced cluster fixed effects into some of their Table 2 and 3 regressions, as a way to deal with time-invariant unobservables in pooled data from the two surveys. Yet using the Stata routine 'geonear' that they reportedly used, we could find only 480 clusters from the 2013 and 2008 surveys met a criteria of the reported lat-lon coordinates being up to 10 km apart despite their claim of having 560 DHS clusters that meet this criteria.

The reported DHS coordinates are randomly displaced, so as to protect confidentiality of survey respondents. The displacement randomizes direction and distance, by up to 2km in urban areas and up to 5 km in rural areas (one percent of clusters are displaced up to 10 km). However, the random displacement is done once by the DHS, prior to the release of geo-coded data, rather re-doing on a bespoke basis for each researcher(s) who requests the data. In other words, the lat-lon coordinates available to us should be the same as what Amare et al (2020) worked with, so the failure to get the same sample size according to their sample description is a concern. Follow-up with the authors suggested that they might have used a 15 km criteria even though it was reported as 10 km in the paper but we found that even with this looser requirement we could not recreate their sample.

Given this inability to recreate their sample, and also because we were not convinced by their cluster fixed effects (particularly once the random displacement is accounted for it is even less likely that clusters from two DHS samples that reportedly are a certain distance apart

[22] The example given in Figure 3, of Wak township and the Kano campus of the Nigerian Law School, which are less than 10 km apart but are very different places, suggests that this is not a very plausible assumption.

are truly the same community) we worked with the full set of DHS clusters in each year. In other words, further follow-up communications and applying more checks to try to recreate the sample of Amare et al (2020) seemed unjustified, especially as there was little we could do with the data from the 2008 survey as VIIRS was not operational in that year.

In addition to these sampling issues, we found that the overall direction of associations between DMSP night lights and anthropometric indicators is opposite to what the Amare et al (2020) discussion suggests. Specifically, we find negative average marginal (partial) effects of the log DMSP values on HAZ, WHZ and WAZ when using the quartic specification (and same control variables) used by Amare et al (2020). Although Amare et al (2020) did not report marginal effects (they only reported coefficients for the quartic polynomial) their discussion emphasizes positive associations of DMSP DN values with the anthropometric indicators, and this discussion is not only for unconditional relationships but also conditional on the same set of control variables that we use. Moreover, what we report in Tables 1 to 3 of this appendix, using pooled 2008 and 2013 DHS and DMSP night lights data and the same set of controls used by Amare et al (2020), shows the same direction of effect that we find in the main body of our paper (especially in Table 4 but also in Table 5), using cross-sectional DHS data for 2013 with either the DMSP or VIIRS night lights data.

For HAZ we find a marginal effect of log DMSP values of -0.67, which is the only marginal effect that is statistically significant amongst the six specifications from linear through to sextic. While our sample size (n=40,957) is larger than the n=33,894 used by Amare et al (2020) the pattern of coefficients on the polynomial terms is highly correlated between what is reported by Amare et al (2020) in their Table 2, and what we report in column (4) of Table 1 in this appendix (r=0.99). It is therefore puzzling that Amare et al (2020) report an overall positive association between DMSP values and HAZ, *ceteris paribus*, yet with a similar set of coefficients on the polynomial terms for the quartic we report a statistically significant negative marginal effect.

The results for WHZ in Table 2 and for WAZ in Table 3 also highlight this puzzle. For the specifications from linear through to quartic, the marginal effects of log DMSP values on WHZ are statistically significantly negative (while they are statistically insignificant for quantic and sextic). The coefficients on polynomial terms in the quartic specification in the model for WHZ have a correlation coefficient of 0.97 with the polynomial terms in Table 2 of Amare et al (2020). In the models for WAZ, the marginal effects are negative and statistically significant for the linear model and the quartic model, and insignificant for the other four models. The coefficients on the polynomial terms for the quartic model have a correlation of 0.99 with the coefficients reported by Amare et al (2020). Thus, it is again a puzzle that similar coefficients could be interpreted as showing positive *ceteris paribus* associations between (log) DMSP values and child weight by Amare et al (2020), while we find negative relationships when using the same data (albeit with a larger sample), and the same control variables and using the same polynomial specifications.

A clear way to sort out issues of non-reproducibility would be for us to post replication datasets for independent investigators to see that the results we report can be obtained from our replication dataset. The same standard could also be asked for with the Amare et al (2020) results. However, there is a constraint in sharing DHS data, because investigators must agree, prior to gaining any DHS data access, to the following stipulation: “re-distribution of any DHS micro-level data, either directly or within any tool/dashboard, is not permitted” (https://www.dhsprogram.com/data/new-user-registration.cfm). Consequently we cannot post a replication data file without violating the terms of the data access for DHS microdata. Instead, as a partial solution to this issue we have made available the do file for creating the following three appendix tables, that use DMSP and DHS data for 2008 and 2013, with links back to the original field names in the DHS data download. Thus, anyone who has the permission to use the DHS microdata could download the Nigeria DHS data from the DHS website, then run our do file on their dataset, in order to establish the transparency of our results. There are no prohibitions on sharing DMSP data, so our DMSP files can also be accessed along with the do file that is hosted at the following github site: https://github.com/NiyiAlimiUoW/Night-lights-and-Nutrition-Replication-Alimi-Boe-Gibson-and-Gibson-

Appd A Table 1: Results for Various Polynomial Specifications Relating HAZ to DMSP Night Lights, Nigeria, Pooled (2008 and 2013 DHS)

Terms in the Polynomial	Values in Amare et al Table 2	Specification of the Polynomial for the Centred Value of the Logarithm of DMSP Night Lights					
		Linear (1)	Quadratic (2)	Cubic (3)	Quartic (4)	Quintic (5)	Sextic (6)
ln (lights) – centred	0.447**	0.0243	0.0376	0.0149	0.4506***	-0.3094	0.3700
	(0.187)	(0.0165)	(0.0241)	(0.0306)	(0.1480)	(0.4429)	(1.1295)
ln (lights) – centred-square	0.084		-0.0101	-0.0609	0.1568*	0.2952**	-0.2340
	(0.061)		(0.0118)	(0.0473)	(0.0851)	(0.1222)	(0.8770)
ln (lights) – centred-cubic	-0.232**			0.0182	-0.3051***	0.2377	-0.0639
	(0.109)			(0.0162)	(0.1082)	(0.3163)	(0.5379)
ln (lights) – centred-quartic	0.058**				0.0725***	-0.2673	0.2573
	(0.026)				(0.0240)	(0.1926)	(0.8549)
ln (lights) – centred-quintic						0.0560*	-0.1558
						(0.0318)	(0.3467)
ln (lights) – centred-sextic							0.0275
							(0.0455)
Year dummy for 2013	0.121***	0.1006***	0.1008***	0.1015***	0.0918**	0.0988**	0.0974**
	(0.036)	(0.0390)	(0.0390)	(0.0389)	(0.0393)	(0.0393)	(0.0395)
Constant	-1.125***	-1.0346***	-1.0098***	-0.9463***	-1.2572***	-0.9360***	-1.1246***
	(0.159)	(0.0949)	(0.0999)	(0.1147)	(0.1503)	(0.2242)	(0.3551)
Average marginal (partial) effects		0.024	0.035	0.126	-0.667**	1.130	-1.036
		(0.017)	(0.022)	(0.085)	(0.276)	(1.027)	(3.540)
F-test for all lights terms=0		2.167	1.315	1.252	3.350	3.290	2.794
p-value for *F*-test on all lights terms		0.141	0.269	0.289	0.010	0.006	0.010
Condition number (multicollinearity)		29.53	30.67	39.26	207.8	1118	6388
Bayesian Information Criteria		169177	169185	169192	169173	169174	169183
Number of observations	33,894	40,957	40,957	40,957	40,957	40,957	40,957

Notes: HAZ is height-for-age *z* score. All regressions include as control variables the child's gender, birth order and age and age squared, the mother's education, the mother's age at first birth, the education of the mother's male partner, the household wealth quintile, and indicators for the household having a TV, for reading newspapers and for visiting family planning agents. Cluster-robust standard errors in ( ), ****p*<0.01, ** *p*<0.05, * *p*<0.10. Amare et al (2020) do not report any diagnostic tests, nor the average marginal (partial) effects which is why those cell values are blank.

Appd A Table 2: Results for Various Polynomial Specifications Relating WHZ to DMSP Night Lights, Nigeria, Pooled (2008 and 2013 DHS)

Terms in the Polynomial	Values in Amare et al Table 2	Specification of the Polynomial for the Centred Value of the Logarithm of DMSP Night Lights					
		Linear (1)	Quadratic (2)	Cubic (3)	Quartic (4)	Quintic (5)	Sextic (6)
ln (lights) – centred	0.106	-0.0777***	-0.0418*	0.0037	0.1441	0.2835	-0.1105
	(0.194)	(0.0194)	(0.0220)	(0.0282)	(0.1631)	(0.5173)	(1.2627)
ln (lights) – centred-square	0.071		-0.0271*	0.0748	0.1450*	0.1196	0.4266
	(0.060)		(0.0144)	(0.0476)	(0.0877)	(0.1409)	(0.9364)
ln (lights) – centred-cubic	-0.274**			-0.0365**	-0.1408	-0.2403	-0.0654
	(0.116)			(0.0173)	(0.1222)	(0.3682)	(0.6046)
ln (lights) – centred-quartic	0.011				0.0234	0.0857	-0.2186
	(0.029)				(0.0282)	(0.2339)	(0.9380)
ln (lights) – centred-quintic						-0.0103	0.1125
						(0.0400)	(0.3838)
ln (lights) – centred-sextic							-0.0159
							(0.0513)
Year dummy for 2013	-0.370***	-0.4762***	-0.4758***	-0.4772***	-0.4803***	-0.4816***	-0.4808***
	(0.160)	(0.0360)	(0.0357)	(0.0357)	(0.0357)	(0.0357)	(0.0357)
Constant	-0.784***	-0.8149***	-0.7481***	-0.8752***	-0.9755***	-1.0344***	-0.9250**
	(0.160)	(0.0786)	(0.0859)	(0.1023)	(0.1483)	(0.2561)	(0.4064)
Average marginal (partial) effects		-0.078***	-0.050**	-0.235***	-0.490*	-0.820	0.437
		(0.019)	(0.020)	(0.093)	(0.300)	(1.241)	(3.924)
F-test for all lights terms=0		16.02	8.474	5.907	4.942	3.978	3.440
p-value for F-test on all lights terms		0.000	0.000	0.001	0.001	0.001	0.002
Condition number (multicollinearity)		29.53	30.67	39.26	207.8	1118	6388
Bayesian Information Criteria		156082	156069	156058	156064	156074	156084
Number of observations	33,894	40,957	40,957	40,957	40,957	40,957	40,957

Notes: WHZ is weight-for-height z score. For other notes see the notes to Appd A Table 1.

Appd A Table 3: Results for Various Polynomial Specifications Relating WAZ to DMSP Night Lights, Nigeria, Pooled (2008 and 2013 DHS)

	Values in Amare et al Table 2	Specification of the Polynomial for the Centred Value of the Logarithm of DMSP Night Lights					
Terms in the Polynomial		Linear (1)	Quadratic (2)	Cubic (3)	Quartic (4)	Quintic (5)	Sextic (6)
ln (lights) – centred	0.290*	-0.0383**	-0.0067	0.0094	0.3464**	0.0318	0.3075
	(0.171)	(0.0168)	(0.0207)	(0.0279)	(0.1523)	(0.4678)	(1.1249)
ln (lights) – centred-square	0.073		-0.0238*	0.0122	0.1806**	0.2379*	0.0232
	(0.054)		(0.0124)	(0.0449)	(0.0824)	(0.1320)	(0.8858)
ln (lights) – centred-cubic	-0.158			-0.0129	-0.2631**	-0.0384	-0.1607
	(0.102)			(0.0160)	(0.1135)	(0.3337)	(0.5229)
ln (lights) – centred-quartic	0.036				0.0561**	-0.0846	0.1283
	(0.025)				(0.0259)	(0.2124)	(0.8628)
ln (lights) – centred-quintic						0.0232	-0.0627
						(0.0362)	(0.3595)
ln (lights) – centred-sextic							0.0111
							(0.0484)
Year dummy for 2013	-0.187***	-0.2761***	-0.2757***	-0.2762***	-0.2837***	-0.2808***	-0.2814***
	(0.030)	(0.0327)	(0.0325)	(0.0326)	(0.0328)	(0.0326)	(0.0327)
Constant	-1.323***	-1.3527***	-1.2939***	-1.3388***	-1.5794***	-1.4464***	-1.5229***
	(0.139)	(0.0690)	(0.0740)	(0.0920)	(0.1349)	(0.2298)	(0.3527)
Average marginal (partial) effects		-0.038**	-0.014	-0.079	-0.693***	0.051	-0.828
		(0.017)	(0.019)	(0.084)	(0.281)	(1.119)	(3.566)
F-test for all lights terms=0		5.197	3.729	2.527	3.179	2.584	2.254
p-value for *F*-test on all lights terms		0.023	0.024	0.056	0.013	0.025	0.036
Condition number (multicollinearity)		29.53	30.67	39.26	207.8	1118	6388
Bayesian Information Criteria		141504	141488	141494	141471	141478	141488
Number of observations	33,894	40,957	40,957	40,957	40,957	40,957	40,957

Notes: WAZ is weight-for-age *z* score. For other notes see the notes to Appd A Table 1.