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**A Test of DMPS and VIIRS Night Lights Data
for Estimating GDP and Spatial Inequality
for Rural and Urban Areas**

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Working Paper in Economics 11/19

September 2019

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Abstract

Night lights, as detected by satellites, are increasingly used by economists, especially to proxy for economic activity in poor countries. Widely used data from the Defense Meteorological Satellite Program (DMSP) have several flaws; blurring, top-coding, lack of calibration, and variation in sensor amplification that impairs comparability over time and space. These flaws are not present in newer data from the Visible Infrared Imaging Radiometer Suite (VIIRS) that is widely used in other disciplines. Economists have been slow to switch to these better VIIRS data, perhaps because flaws in DMSP are rarely emphasized. We show the relationship between night lights and Indonesian GDP at the second sub-national level for 497 spatial units. The DMSP data are not a suitable proxy for GDP outside of cities. Within the urban sector, the lights-GDP relationship is twice as noisy using DMSP as using VIIRS. Spatial inequality is considerably understated by the DMSP data. A Pareto adjustment to correct for top-coding in DMSP data has a modest effect but still understates spatial inequality and misses much of the intra-city heterogeneity in the brightness of lights for Jakarta.

JEL Codes

O15, R12

Keywords

density
DMSP
inequality
night lights
VIIRS
Indonesia

Acknowledgements

This paper was written while Gibson was visiting the Centre for the Study of African Economies, Department of Economics, University of Oxford, whose hospitality he acknowledges. The views in this paper are those of the authors.

I. Introduction

Night lights, as detected by satellites, are increasingly used by economists, especially to proxy for economic activity in poor countries. A recent review finds more than 150 studies in economics using night lights, almost all of which use the Defense Meteorological Satellite Program (DMSP) data even as there is a rapid switch to using newer and better data from the Visible Infrared Imaging Radiometer Suite (VIIRS) in other disciplines (Gibson *et al.* 2019). Flaws in DMSP data include blurring, coarse resolution, no calibration, low dynamic range, top-coding, and unrecorded variation in sensor amplification that impairs comparability over time and space (Elvidge *et al.* 2013, Abrahams *et al.* 2018, Bluhm and Krause 2018).

Many of these flaws stem from the original purpose of DMSP, which was to detect clouds to assist with short-term weather forecasts for the Air Force. In contrast, the VIIRS Day-Night Band (DNB) was designed to help researchers consistently measure the radiance of light coming from earth, in a wide range of lighting conditions (covering almost seven orders of magnitude while DMSP covers less than two), with high spatial accuracy and with temporally comparable data. The superiority of VIIRS has resulted in a rapid switch in the scientific literature and now almost twice as many articles per year publish using the VIIRS night lights data compared to those using the older and less suitable DMSP data, even while economists increasingly use DMSP data and largely ignore VIIRS (Gibson *et al.* 2019).

The continued, and even rising, use of DMSP data by economists reflects several factors. First, there has been a larger scholarly impact, in terms of citations, from studies such as Henderson *et al.* (2012) that suggest that DMSP lights data can be used successfully in a wide range of circumstances, than for studies such as Chen and Nordhaus (2011) that are far more limited in the support they offer for using DMSP data.¹ Second, the DMSP data have a long time series, from 1992 to 2013, which may be attractive to economists. Two caveats to that potential advantage are that night lights are a much better predictor of GDP and other economic variables cross-sectionally than temporally (Addison and Stewart 2015, Nordhaus and Chen 2015), and the time series will become outdated, with the DMSP data stopping in 2013 while the VIIRS data are available monthly with only a slight lag.² A third reason why economics may be slower to switch to using VIIRS night lights data, compared to other disciplines, is that flaws in the DMSP data are rarely highlighted in the economics literature. While the remote sensing literature has several comparisons that highlight the superiority of VIIRS (for example, Elvidge *et al.* 2013) and sometimes even in studies authored by economists (for example, Chen and Nordhaus 2019), there are no similar studies in economics journals.

¹ Specifically, Chen and Nordhaus (2011, p.8594) noted that ‘luminosity data do not allow reliable estimates of low-output-density regions’ and that only for countries with the worst statistical systems, accounting for under nine percent of world population, are night lights data likely to add value as a proxy for economic output.

² At the time of writing (September, 2019) the monthly VIIRS data were available from April 2012 to June 2019 from https://eogdata.mines.edu/download_dnb_composites.html.

In light of the limited comparisons between DMSP and VIIRS within economics, the current paper presents a test of these data for estimating regional GDP and inequality for rural and urban areas. Specifically, we estimate relationships between night lights and Indonesian GDP at the second sub-national level for 497 spatial units. Indonesia is one of few developing countries with reliable GDP data at the second sub-national level, and it is for such countries that night lights data are potentially the most useful, given more abundant data available for richer countries. We find the DMSP data are not a suitable proxy for GDP outside of cities, with a statistically significant negative relationship between real GDP and DMSP lights for the 399 spatial units that are rural. This echoes a finding of Keola *et al.* (2015), whose cross-country analysis showed the relationship of DMSP night lights to GDP was negative where and when agriculture is a large share of GDP, even as it is positive elsewhere.

While there is a positive relationship between lights and GDP in Indonesia's urban sector, the lights-GDP relationship is twice as noisy if estimated with DMSP data rather than VIIRS. We also find that spatial inequality is considerably understated by the DMSP data, especially in the urban sector. While a Pareto adjustment developed by Bluhm and Krause (2018) to deal with top-coding in DMSP data has a modest effect, the adjusted data still understate spatial inequality and miss much of the intra-city heterogeneity in the brightness of lights for Jakarta.

II. Background and Related Literature

Researchers have used night lights data from the Defense Meteorological Satellite Program Operational Linescan System (DMSP for short) for over 40 years, even though these satellites were designed to observe clouds for short-term weather forecasts rather than to give a consistent long-term record of lights on earth. While a few earlier studies by remote sensing researchers had an economics focus, it was not until Henderson *et al.* (2012), and to a lesser extent Chen and Nordhaus (2011), developed ways to optimally weight data on night lights and reported GDP, in order to predict true GDP, that many economists paid attention to night lights data.³ These key studies noted that the night lights data were noisy but concluded that in a fairly wide range of contexts (Henderson *et al.* 2012), or, alternatively, in a narrower set of contexts (Chen and Nordhaus 2011), DMSP lights data could add value to conventional economic statistics like national and regional GDP. A few subsequent studies in economics highlighted noise in DMSP data, with low explanatory power and unstable growth elasticities for long differenced economic variables (Addison and Steward 2015), greater uncertainty in lights-based time-series of GDP estimates than for cross-sections of GDP (Nordhaus and Chen 2015), and unstable relationships between DMSP data and regional GDP making the DMSP data a poor proxy for regional economic activity (Bickenbach *et al.* 2016).

³ While Chen and Nordhaus (2011) is clearly an economics contribution, it is not in an economics journal and only one-quarter of the 500 citations (in *Google Scholar* as of Sept 9, 2019) are from economics journals or working papers. In contrast, far more of the 1200 citations to Henderson *et al.* (2012) are from economics, so most economists with exposure to night lights data will have gained this through Henderson *et al.* (2012).

Despite these critical findings, many more studies in applied economics have used the DMSP data to study a wide range of topics (see Gibson *et al.* 2019 for a selective survey). It was not until more recently, in Abrahams *et al.* (2018) and Bluhm and Krause (2018), that the measurement errors in the DMSP data were more fully linked to some inherent flaws in the sensors and data processing, and that possible correction methods were proposed. We briefly summarize some of these flaws, and contrast DMSP with features of the Day-Night Band (DNB) of the Visible Infrared Imaging Radiometer Suite (VIIRS), which is a more accurate source of night lights data from the *Suomi* satellite that was launched in 2011.

The DMSP data lack spatial accuracy because the sensor and data processing attribute light to different places than where it was emitted. Some earlier studies suggested this was from reflection off water or snow, and so may matter in only a few places, but recent studies show that ‘blurring’ is an inherent feature of DMSP data (Abrahams *et al.* 2018). The DMSP satellite orbit altitude is about 800 km, which is just over one-quarter of the 3000 km sweep of the sensor, and so except at the nadir the earth is viewed at an acute angle, giving a larger field-of-view (four-fold larger at the edge) from which all light is attributed to a smaller pixel in the centre. The on-board computers are unable to hold the data for all the small pixels, so aggregate to 5×5 blocks (of size 2.7 km × 2.7 km at the nadir) prior to the data being sent to earth, which further spreads light from its point of origin.

Random geo-location errors, with a mean of about three km, further spread apparent sources of light. In contrast, VIIRS has a near-constant spatial resolution across the sweep of the sensor, by compensating for the expanded ground footprint as the scan goes towards the edge, and handles finer 0.7 km × 0.7 km pixels due to abundant data storage. Spatial errors in DMSP data show up as exaggerated estimates of lit area for cities; Gibson *et al.* (2019) show a 150% error for Dar es Salaam, and errors of 500% or more for smaller towns. Abrahams *et al.* (2019) find that DMSP data overstate city area by an average of 77% across 15 big cities. In overstating the lit area of cities, DMSP data are wrongly attributing light to hinterland areas, introducing cross-sectional noise.

The lack of temporal consistency of DMSP data, which causes errors in time-series of lights-based GDP estimates, is from two main sources. First, there is no on-board calibration, with changes in the sensor amplification over the monthly lunar cycle – *gain settings* – not recorded in the data. The signal is amplified going into the dark part of the month to keep the brightness of moon-lit cloud tops the same, so lights on earth then appear brighter, but no record is kept to allow *ex post* adjustment to give consistency (Hsu *et al.* 2015). The number of nights whose images meet the quality controls needed to be included in the DMSP annual composites varies widely over time and space, due to factors like cloudiness (especially near the equator), so convergence to an average amplification level that might provide comparable data over time (and space) is unlikely (Gibson *et al.* 2019). This lack of temporal consistency in the DMSP data is exacerbated by the limited on-board data storage, with continuous measures converted to 6-bit integers (the Digital Number (DN) that ranges from 0-63, as $2^6=64$), that are subject to censoring from the top and the bottom (Abrahams *et al.* 2018).

A lack of calibration for DMSP also shows up as inter-satellite differences. For 12 of the 22 years (from 1992 to 2013) with annual composites of DMSP lights available, two satellites are in orbit providing data, and they often report different values for the same place. For example, for a place (Sicily), with little temporal variation, Gibson *et al.* (2019) show that satellite F12 gave 29% higher DN values than F14 in the overlapping years, F15 recorded a 24% decline in the DN value from 2002 to 2003 while F14 showed just a 2% change in the same year, and F18 gave a 32% higher DN value in 2010 than was seen with F16 in 2009.⁴ These inter-satellite differences and the unrecorded variation in sensor amplification (in conjunction with time-space variation in how many nights contribute to annual composites, which limits convergence to some average amplification level) means that a DN value from a certain satellite year may not refer to the same brightness as the same DN from another year. In contrast to temporal consistency problems with DMSP, the VIIRS sensors are calibrated radiometers, where data provided by the instrument are proportional to the intensity of light (in nanoWatts/cm²/sr). The VIIRS sensors have in-flight calibration to ensure that data are comparable over time and space, and even when the continuous signal is quantized, it is with 14-bit precision ($n=16,384$) compared to the 6-bit Digital Number for DMSP.

Further flaws in DMSP data stem from the limited dynamic range of the sensors. The brightest lights in the CBD of cities often are given the same digital number (usually DN=63) as the less brightly-lit suburbs (Bluhm and Krause 2018). This is because the dynamic range of the DMSP sensor is less than two orders of magnitude, and so it cannot simultaneously capture light from brightly lit areas and from dimly lit areas. Under usual conditions, when the sensor amplification is turned up to view cloud tops, pixels in city centres are saturated with light and get the top-coded DN value of 63.⁵ In contrast, the dynamic range of the VIIRS Day-Night Band is about seven orders of magnitude ($L_{\max}/L_{\min}=6,700,000$) and so there are no saturation problems with VIIRS data. Bluhm and Krause (2018) suggest that lights follow a Pareto distribution, and use this to adjust DMSP data for top-coding; while the VIIRS data are not used in their correction method, they use these more accurate data to corroborate that the top tail of pixels in the night lights distribution follows a Pareto process.

In addition to these flaws in the DMSP data, it is becoming clear that satellite data on night lights (including from VIIRS) are poorly suited to the study of areas of low population density, which includes most rural places. One reason is that the sort of lights typically used in rural villages are not the type easily detectable from space. An experiment on accuracy of

⁴ Significantly higher values from F18 than F16, when recording the exact same light source on the same night (from an experiment using portable generators to power high-pressure sodium lamps in previously dark areas) is also noted by Tuttle *et al.* (2014).

⁵ Based on experiments when researchers had the Air Force lower the DMSP sensor amplification on a few nights to avoid DN values being top-coded, there are radiance-calibrated lights available for seven years. These rely on pre-flight calibrations of the satellites, rather than their degraded (from exposure to radiation) actual performance, and require merging with the usual DMSP data so as to create annual composites (Hsu *et al.* 2015), which seems to create some instability between years (Bluhm and Krause 2018).

DMSP data, where researchers lit up previously dark areas, needed 1000-watt high pressure sodium lamps (large lamps of about 25 kg each, usually used in big warehouses), modified with aluminum shields used to direct light skywards (Tuttle *et al.* 2014) in order to be seen with the DMSP sensors. This sort of light is not at all like what is found in rural villages, but is more like light from concentrated street lamps and industrial facilities, which are typically found in urban areas. While VIIRS can better detect dimly-lit areas, the overpass time when the satellite observes light is around 1.30am, and lights coming from the household sector in rural areas are unlikely to be switched on then (while urban street lights stay on all night).

There are several examples of this inability to detect low density areas. Nordhaus and Chen (2015) divided the globe into $1^{\circ} \times 1^{\circ}$ grid cells and found that almost one-third of cells with positive population and output were recorded as having zero light in the DMSP data. In a follow-up focused on Africa, they show that the odds of DMSP finding no light rise as cell population density falls, and that while VIIRS has better detection rates, the elasticity of gross cell product with respect to VIIRS lights is higher for the densely populated cells (Chen and Nordhaus 2015). Even just focusing on cities and towns in Africa, detection rates using the DMSP and VIIRS satellites are only 40-45% (Andersson *et al.* 2019).

Gibson *et al.* (2019) provide examples from developing countries in Africa, Asia and the Pacific, where low density areas, home to up to 70% of the population, are not detected by either DMSP or VIIRS, even when more than half of households in those areas use electric lights. They also highlight the case of Vanuatu, where a seasonal migration program lifted participant incomes by up to 40%, had large aggregate effects, and prompted a switch into using electric lights (as seen in census data) but these development impacts were invisible in data from either DMSP or VIIRS. At a more aggregate level, using a cross-country panel to study relationships between night light (annual composites of DMSP lights) and national GDP, Keola *et al.* (2015) find positive elasticities of light with respect to GDP for countries where the agricultural share of GDP is less than 20% but negative relationships when the agricultural share of GDP exceeds 20%. The authors note that it is possible for agriculture's value-added to increase without an increase in lights, while the same is much less true for the urban sector.

III. Data and Methods

In light of the above discussion of related literature, comparing performance of DMSP data and VIIRS data for predicting regional GDP may be useful. The results should consider urban and rural sectors separately, given the sectoral differences in density of population and economic activity that likely affect the performance of the satellites in detecting night lights. One issue with such a test is the limited temporal overlap of the two data sources. The DMSP data are only available annually, with the time-series ending in 2013. While VIIRS data are available in a monthly time-series from April 2012, there is potential to introduce extraneous elements if monthly and annual data are compared. For example, not only are there seasonal differences, the annual composites (for both DMSP and VIIRS) undergo further processing by scientists at

the Earth Observation Group of the National Oceanic and Atmospheric Administration (NOAA) to screen out ephemeral lights and background (non-lights). Thus, the average of the monthly VIIRS data would not be comparable to the annual composite of either VIIRS or DMSP data because the monthly data do not undergo this screening process. Therefore, to ensure the closest like-with-like comparison, we restrict attention to the annual composites provided by NOAA. This limits the length of the time-series and so we chose to work on Indonesia, as a developing country that provides a lot of cross-sectional variation and that also has reliable regional GDP data that we can use as our benchmark.⁶

Our research design relies on the fact that the second sub-national level in Indonesia is comprised of two types of spatial units. The first is *Kabupaten* (regencies), that are mainly rural areas and towns and have a mean (median) population density of 280 (83) persons per square kilometre. The other type of spatial unit is *Kota* (cities), which are highly urbanized and have a mean (median) population density of 3900 (2200) persons per km² in the 2010 census. These are quite populous spatial units, with the average *Kota* having a population of 530,000 and the average *Kabupaten* having 460,00 in 2010; 22% of Indonesia's population is located in *Kota* (of which there are $n=98$) and the rest are in the *Kabupaten* ($n=399$).⁷ Any detection problems, or poorly fitting predictor equations for GDP, for such populous units would be expected to be exacerbated if smaller units were used.

We use three data sources to test the relationship between night lights and Indonesia's second-level sub-national GDP. The first is VIIRS annual composites for 2015 and 2016, that are the earliest (and currently only) available annual composites. We use the 'vcm-orm-ntl' product that, at the pixel level, excludes nights where Day-Night Band images are affected by stray light or by clouds. These annual composites also have outliers removed by the NOAA scientists, where these outliers may be due to ephemeral sources of light, such as fires or fishing boats, and the background (that is, non-lights) is set to zero. The data are radiance values in units of nano Watts per square cm per steradian (nanoWatt/cm²/sr) and range from zero to about 1600 for Indonesia.

The second data source is DMSP annual composites for 2011 and 2012, also from NOAA (for example, for 2012 the file is F182012_v4b_stable_lights.avg_vis.tif). The F18 satellite providing these images has a 4-year time series starting in 2010. A feature of DMSP data is that the first and last year of the time series for each satellite often have fewer nights whose images contribute to the annual composite (Gibson *et al.* 2019), and so we use the middle two years to provide the most reliable annual estimates. This also helps maintain comparability

⁶ This research design also plays to the strength of night lights, which have been shown to be far better at predicting GDP in the cross-section, than at predicting the growth of GDP in the time-series (Nordhaus and Chen 2015, Chen and Nordhaus 2019).

⁷ We use the administrative geography from 2010, and where spatial units subsequently split we re-aggregate them to have a temporally consistent set of 497 spatial units.

with the VIIRS data that are also for two years. The DMSP data are digital numbers, ranging from 0-63, and have no interpretation in terms of radiance values.

The third data source is data on the Gross Regional Domestic Product (GRDP) from the Indonesian government's Central Bureau of Statistics (BPS). The BPS calculate and report GRDP at both the provincial level, and the next level down (*Kabupaten/Kota*). The data for provincial-level GRDP are available from 1975 onwards, whereas those for the second sub-national level that we use are available only from 1993 onwards. For the purpose of this paper, we utilize the GRDP data from 2011-2016, that are in spatially and temporally real terms, and use a 2010 base.

In preparing the data for econometric analysis, we had to deal with 17 *Kabupaten* in 2011, and those same 17 plus three more in 2012, where no light was detected by the DMSP sensors. These areas are in the most sparsely populated eastern provinces of Indonesia. Two of these *Kabupaten* also had no light detected by VIIRS in 2015, with two more undetected in 2016. We therefore used the inverse-hyperbolic-sine transformation for the lights data, which is identical to using logarithms for the non-zero observations, but also lets us use those with zeros without resorting to transformations like adding one to all values before logging (Gibson et al, 2017). We use logs of the real GDP values, so that our regression coefficients can be interpreted as elasticities (noting that the units of the DMSP data – DN values – are not comparable to the VIIRS radiance units so we need to use unit-free elasticities).

IV. Results

There is no statistically significant relationship between DMSP data on night lights and real GDP for the 497 regions at Indonesia's second sub-national level, with an elasticity of -0.059 from the pooled regression that is surrounded by a wide standard error (Table 1). The same result holds in a purely cross-sectional, year-by-year analysis, where the elasticities are -0.081 and -0.039. In contrast, using VIIRS data gives precisely estimated elasticities of between 0.17 and 0.18 when using the night lights to predict real regional GDP.

When the regressions are estimated separately for the *Kabupaten* (which covers the rural sector and some towns) and the *Kota* (which covers cities) it is apparent that the prior results aggregate over very different relationships. For the lower density regions that are administered as *Kabupaten*, real GDP is negatively, and statistically significantly, related to DMSP night lights, with an elasticity of -0.11. In contrast, the elasticity for city GDP with respect to DMSP night lights is 0.94 in the pooled regression, or ranges from 0.86 to 1.02 in the year-by-year regressions. This sectoral gap – which reflects the sectoral differences in density of population and economic activity – is also seen in the differences in the degree of predictive fit, with the between- R^2 values (which greatly exceed within- R^2 , supporting the idea that lights better proxy for economic activity in the cross-section than for time-series changes) much higher for the urban *Kota* than for the more rural *Kabupaten*.

**Table 1: The Predictive Power of Night Lights for Regional GDP
is much higher with VIIRS than with DMSP and is much higher for Cities**

	DMSP 'stable lights' for 2011 and 2012			VIIRS Annual Composites for 2015 and 2016		
	All spatial units (Urban & Rural)	<i>Kabupaten</i> (Mainly Rural)	<i>Kota</i> (Cities)	All spatial units (Urban & Rural)	<i>Kabupaten</i> (Mainly Rural)	<i>Kota</i> (Cities)
<i>Pooled regressions</i>						
Log (sum of lights) _{it}	-0.059 (1.44)	-0.107*** (2.72)	0.939*** (7.78)	0.179*** (3.34)	0.086 (1.55)	0.936*** (16.76)
Year 2 dummy	-0.008 (0.08)	-0.005 (0.05)	-0.123 (0.71)	0.056 (0.61)	0.045 (0.43)	0.056 (0.47)
Constant	2.786 (7.59)	3.125 (8.80)	-5.734 (5.05)	1.041 (1.40)	1.704 (3.84)	-5.290 (10.54)
R² overall	0.01	0.03	0.36	0.05	0.01	0.68
<i>R² within</i>	0.00	0.00	0.00	0.00	0.00	0.00
<i>R² between</i>	0.01	0.03	0.38	0.05	0.01	0.69
Number of observations	994	798	196	994	798	196
<i>Year-by-Year Regressions</i>						
Log (sum of lights) _{it=1}	-0.081 (1.43)	-0.130** (2.41)	0.858*** (4.44)	0.185** (2.48)	0.093 (1.19)	0.945*** (12.36)
Constant	2.969 (5.89)	3.310 (6.87)	-5.028 (2.83)	0.992 (1.65)	1.658 (2.69)	-5.366 (7.83)
R²	0.01	0.04	0.30	0.05	0.01	0.69
Log (sum of lights) _{it=2}	-0.039 (0.66)	-0.086 (1.52)	1.024*** (7.39)	0.172** (2.25)	0.080 (1.00)	0.927*** (11.34)
Constant	2.607 (4.97)	2.947 (5.79)	-6.618 (5.13)	1.144 (1.88)	1.794 (2.88)	-5.158 (7.05)
R²	0.00	0.02	0.43	0.05	0.01	0.68
Number of observations	497	399	98	497	399	98

Notes

The dependent variable is log real GDP for the *Kabupaten* or *Kota* (in 2010 prices and using the administrative divisions from 2010 to account for subsequent splitting of spatial units). The *t*-statistics in () are from robust standard errors, ***, **, and * denote statistical significance at 1%, 5% and 10% levels.

If the VIIRS data are used to predict the GDP of spatial units, the elasticities are all positive, unlike for DMSP. However, for the *Kabupaten*, the elasticities are only about 0.08 to 0.09, and are imprecisely estimated. In contrast, for the urban *Kota*, the elasticities are from 0.93 to 0.95, and are very precisely estimated. Thus, satellite observation of night lights does not appear to be a suitable source of data to proxy for GDP outside of cities. Another contrast in Table 1 concerns the noise in the lights-GDP relationship for the urban sector. The unexplained share of the variation in real GDP is twice as large when using DMSP to predict GDP, at 64%, compared to using VIIRS where it is only 32% (for the overall R^2 values). Finally, there is more year-by-year variation in the regression coefficients when using DMSP data rather than VIIRS data; this time-series instability likely reflects lack of calibration in DMSP data which means that DN values in one year are not necessarily comparable to those in another year.

The DMSP data considerably understate spatial inequality. In Table 2 we report the Gini coefficient and Theil index for spatial inequality in lights, estimated over all 497 spatial units, and then separately for *Kabupaten* and for *Kota*. Considering first results for the Theil index, which is sensitive to inequality at the top of the distribution, inequality according to the VIIRS data is 53% higher (with a Theil index of 2.19) than according to the DMSP data (with a Theil index of 1.42). This difference is especially coming from the urban areas, where the VIIRS data show 64% higher inequality than do the DMSP data. We expand upon this comparison in Figure 1, which shows the Lorenz curve for lights in urban areas according to the DMSP data and the VIIRS data. Using the DMSP data, the Lorenz curve is significantly closer to the line of equality at all points, and yields a Gini coefficient of 0.58 compared to the Gini of 0.71 using VIIRS (the difference is statistically significant).

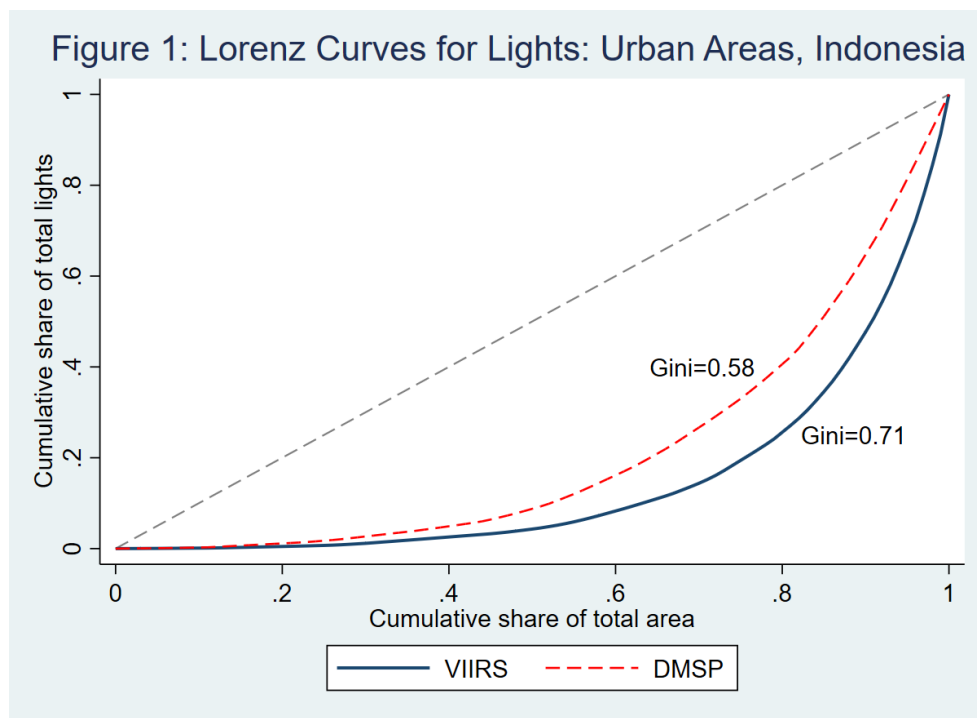


Table 2: DMSP Data on Night Lights Considerably Understate Spatial Inequality even after Pareto Adjustment for Top-Coding

	Gini Coefficient			Theil Index		
	All Spatial Units (Urban & Rural)	<i>Kabupaten</i> (Mainly Rural)	<i>Kota</i> (Cities)	All Spatial Units (Urban & Rural)	<i>Kabupaten</i> (Mainly Rural)	<i>Kota</i> (Cities)
DMSP (2011-12)	0.798 (0.017)	0.777 (0.016)	0.575 (0.059)	1.424 (0.089)	1.276 (0.076)	0.565 (0.123)
DMSP (Pareto-adjusted for top-coding)	0.809 (0.016)	0.781 (0.015)	0.640 (0.044)	1.542 (0.092)	1.305 (0.077)	0.753 (0.120)
VIIRS (2015-16)	0.860 (0.014)	0.803 (0.019)	0.705 (0.041)	2.185 (0.129)	1.527 (0.127)	0.929 (0.134)
Number of observations	497	399	98	497	399	98

Notes

Standard errors in ().

Inequality statistics based on the share of total lights and of total area from each spatial unit.

Real GDP data for the same spatial units show no change in spatial inequality from 2011-12 to 2015-16.

The inequality estimates are based on two-year sums of lights, so that cross-sectional patterns are highlighted, and as these are not for overlapping periods (2011-12 for DMSP and 2015-16 for VIIRS) it is possible that there was some change in underlying spatial inequality for Indonesia, that weakens the comparisons shown in Figure 1 and Table 2. However, the GDP data show no evidence of this, with just a two percent change (a slight fall) in spatial inequality from 2011-12 to 2015-16 according to the Theil index (and no change in the Gini). Thus, even without overlapping data we can conclude that using DMSP data will understate spatial inequality, especially for urban areas, and especially at the top of the distribution (the understatement of the Gini coefficient is proportionately less than for the Theil index).

Several of the flaws in DMSP data could cause spatial inequality to be understated. The blurring and spatial errors will tend to spread the apparent lights into neighboring units, causing a reversion to the mean and understating inequality. The top-coding of DN values at 63 will also dampen inequality, particularly at the top of the distribution. To study which source of error may matter most, we use the Pareto-adjusted DMSP values for 2011 and 2012 that have been derived by Bluhm and Krause (2018) and are made available at their website: <http://lightinequality.com/top-lights.html>. We re-estimate the Table 2 inequality statistics and find that the Pareto-adjustment for top-coding closes about one-fifth of the gap between the results from DMSP and VIIRS, in terms of overall inequality (for example, raising the Theil index from 1.42 to 1.54, compared to the value of 2.19 with VIIRS). The Pareto adjustment closes relatively more of the gap in inequality estimates for urban areas (for example, closing 45% of the gap in the Gini between the original DMSP estimates and the benchmark VIIRS estimates). While this is a promising finding, it remains the case that spatial inequality is substantially understated, even when using the Pareto-adjusted DMSP data.

The inequality described in Figure 1 and Table 2 considers the urban sector as a whole, but night lights also are used to study *intra*-city differences (for example, Kocornik-Mina *et al.* 2019). The top-coding and limited dynamic range of DMSP may distort understanding of spatial patterns in the development of particular cities by disguising the differentiation that occurs in certain places. We illustrate this effect in Figure 2, which maps night lights in Jakarta (restricting attention to the area within the administrative boundaries of the city). The DMSP stable lights for 2012 in Panel (a) show very little *intra*-city heterogeneity; 82% of the pixels have a digital number (DN) value of 63 (the highest possible) and 17% have DN=62. With such data, one cannot see where within a city the lights are brightest, and by treating all areas as roughly equally bright the DN values are almost like a dummy variable for whether a pixel is part of the city or not. This limited variation may explain a finding of Gibson *et al.* (2017) that decomposing the sum of lights from cities into the extensive margin (the lit area) and intensive margin (the brightness of the lit area) shows that only growth on the extensive margin predicts their outcome of interest (poverty rates in rural India). With DMSP data not giving plausible measures of brightness variations within cities, a more appropriate research design for such data may be to rely on simpler indicators, like the 0/1 variable of whether a pixel is lit brightly enough to be considered part of the city or not.

The map in Panel (b) of Figure 2 shows the intra-city patterns in the Pareto-adjusted DMSP data for 2012 provided by Bluhm and Krause (2018). With this adjustment, the most brightly-lit core of the city appears as an approximately rectangular area, running about 8 km in a north-south direction and 6 km in an east-west direction, located slightly left of center, with a moderately lit area to the northeast (going towards Jakarta Bay). The remainder of the city appears as a largely undifferentiated area with low levels of light recorded. The adjusted data roughly locates the CBD but a comparison with the map in Panel (c), that is based on the more accurate VIIRS images, shows that important details are missed in the Pareto-adjusted data. In the VIIRS images, the most brightly lit pixels form less of a block, and run more northeasterly towards the port of Tanjung Priok, which is the concentrated block of bright lights towards the upper right of the map. The brightness of the port is entirely missed in the Pareto-adjusted DMSP images, despite this large and long-standing port covering almost 200 hectares (2 km²) and handling one-third of Indonesia's cargo (outside of oil and gas). The Pareto-adjusted DMSP data also miss spots of brightly lit areas in east Jakarta, and miss the development towards the northwestern edge of the city, on the way to the Soekarno-Hatta airport (that is just outside the city administrative boundary). Thus, while the Pareto-adjusted images improve over the usual DMSP data that portray most of the city as an undifferentiated blob of light, they still seem to miss much of the detail and therefore may provide a poor guide to patterns of intra-city spatial heterogeneity.

In addition to the location errors, of the Pareto-adjusted data missing some spatial patterns, the range of values created when replacing the top-coded DN values of 63 may overstate the brightness differences. To allow for a quantitative analysis to supplement the visual comparison offered in Figure 2, we laid a grid of 590 cells over the maps in Figure 2 and calculated cell-level statistics so that we could compare reports of light coming from the same small areas.⁸ The coefficient of variation (CoV) of the Pareto-adjusted DMSP data is 60% above the CoV for VIIRS data (Table 3), which suggests that the adjustment introduces more variability – in the sense of a wider range of values – than found in the actual measures of radiance (Table 3). This relatively poor correspondence between the Pareto-adjusted data and the VIIRS radiance measures also shows up in Figure 3, which provides a scatter plot of the radiance for each cell, from the VIIRS data, against the DN values for the same cell that comes from the Pareto-adjusted DMSP data.⁹ The R^2 for this relationship is only 0.35 and the elasticity of cell radiance with respect to the cell DN value from the Pareto-adjusted data is 0.54. While this is a better fit than using the original top-coded DMSP data to predict radiance, which has an elasticity of 0.30 and a R^2 of just 0.03, it is still true that there will be a lot of error if the Pareto-adjusted DMSP data are used as a proxy for actual radiance (or to proxy for the underlying differences in economic density producing the spatial patterns in radiance).

⁸ The grid is 30×30, but 310 of the 900 cells fall outside the boundaries of Jakarta, given that the city does not have a perfectly square shape.

⁹ We refer to these data as log transformed in the figure, for simplicity, even though strictly speaking they are inverse-hyperbolic-sine transformed.

Figure 2: Intra-Jakarta Heterogeneity in Night Lights is Obscured When Using DMSP Data, Even With Pareto Adjustment for Top-Coding

(a) DMSP Annual Composite 2012

(b) Pareto-Adjusted DMSP for 2012

(c) VIIRS Outlier Removed Night Lights, 2015

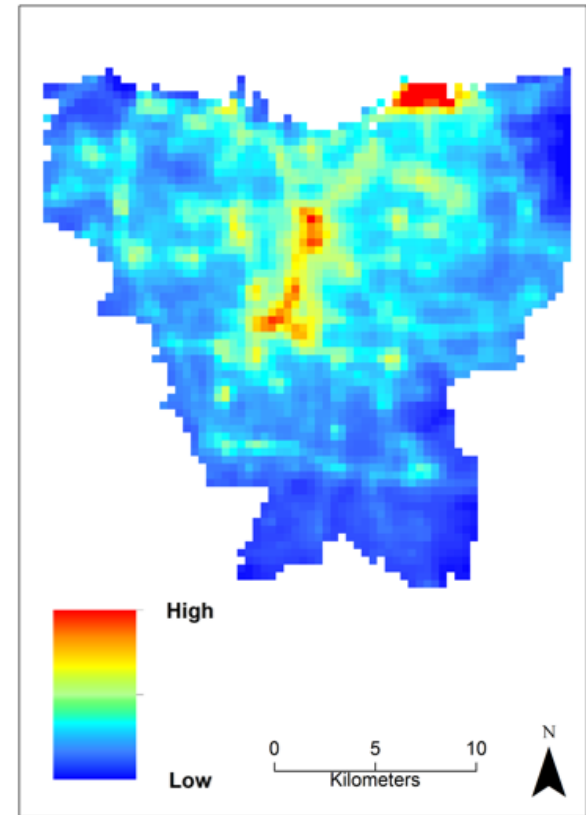
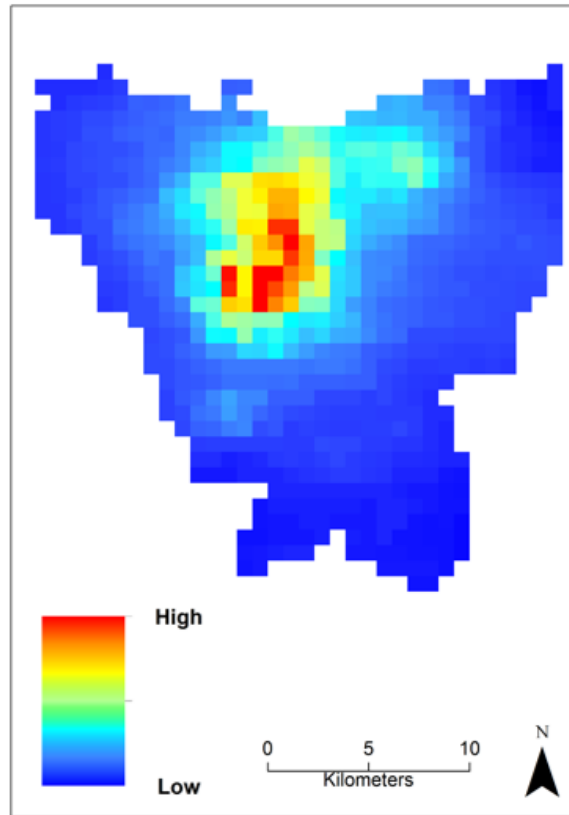
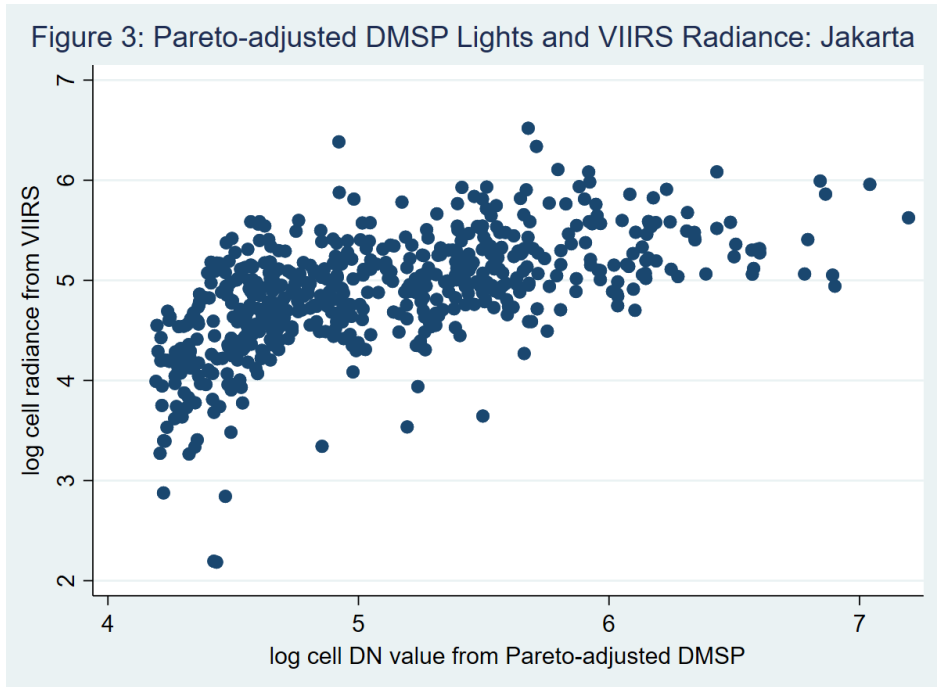


Table 3: Cell-Level Comparisons for Jakarta Night Lights from DMSP and VIIRS

	Coefficient of Variation	Elasticity of Radiance with respect to DN Value	R^2 for Regression of log VIIRS Radiance on log DMSP DN
DMSP (2012)	0.01	0.30 (0.07)	0.03
DMSP (Pareto-adjusted for top-coding)	0.67	0.54 (0.03)	0.35
VIIRS (2015)	0.42	n.a.	n.a.

Notes

There are 590 observations, based on a 30×30 square grid and omitting cells outside of the Jakarta administrative boundaries. Radiance is in nanoWatt/cm²/sr while the DMSP values are just digital numbers. Given the different units, we only report unit-free measures.



V. Conclusions

We use night lights data from DMSP and VIIRS to test the lights-GDP relationship, using data for second level sub-national areas for Indonesia. We find that the DMSP data are not a suitable proxy for GDP outside of cities, with a negative and statistically significant relationship between GDP and the Digital Numbers from DMSP, which echoes previous findings with cross-country data. While the VIIRS data show a positive relationship with GDP outside of cities, the elasticity is low and imprecisely estimated. With these results, and also some awareness of the type of lights needed to be detected by satellite, it seems clear that neither DMSP nor VIIRS are suitable data sources for studying lower density, rural, areas in developing countries.

Within the urban sector, where the lights-GDP elasticity is almost 1.0, we find that the relationship between lights and urban GDP is twice as noisy using DMSP as using VIIRS. In particular, 64% of the spatial variation in urban GDP is unexplained by DMSP data, while only 32% is unexplained when VIIRS data are used. Relatedly, there is a big understatement of spatial inequality when using the DMSP data, especially at the top of the distribution; for example, the Theil index with the VIIRS data shows 64% more inequality than what the DMSP data show. While using a Pareto adjustment to correct for top-coding in DMSP data has a modest effect, even the adjusted data understate spatial inequality and miss much of the intra-city heterogeneity in the brightness of lights for Jakarta.

Applied economists face difficult choices when they want to use data on night lights. They can use the newer and better VIIRS data, but they then have a shorter time-series for relating to economic variables. However, that time-series will only get longer, with launch of the NOAA-20 satellite in November 2017 – which has the identical measuring instruments as on the Suomi satellite that hosts VIIRS. If they, instead, choose to work with DMSP data in order to exploit the longer time-series, they should be aware that the flaws in these data, even when some proposed corrections are applied, may introduce substantial error into their analysis.

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