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Better Night Lights Data, For Longer

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Abstract

Night lights data are increasingly used in applied economics, almost always from the Defense Meteorological Satellite Program (DMSP). These data are old, with production ending in 2013, and are flawed by blurring, lack of calibration, and top-coding. These inaccuracies in DMSP data cause mean-reverting errors. This paper shows newer and better VIIRS night lights data have 80% higher predictive power for real GDP in a cross-section of almost 300 European NUTS2 regions. Spatial inequality is greatly understated with DMSP data, especially for the most densely populated regions. A Pareto correction for top-coding of DMSP data has a modest effect.

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I. Introduction

Satellite-detected night time lights data are increasingly used in applied economics. The first article in an economics journal using these data was in 2002 (Sutton and Costanza, 2002) but it was only once Henderson et al (2011, 2012) published in the *American Economic Review* using night lights that many economists became professionally interested in such data. One indicator of the growing use of these data comes from a search of the economics literature in IDEAS/RePEc, which shows 175 records (articles and working papers) since 2010 have either "night lights" or "night time lights" or "luminosity" in their details.[2] The production of papers using night lights data is increasing, as 41 of these 175 records date from either 2019 or 2020.

There is a problem with much of the economics research using night time lights data. Most studies use the Defense Meteorological Satellite Program (DMSP) data, which are old and not very accurate. For example, of the 41 IDEAS/RePEc records from 2019 or 2020, all but four use DMSP data. The inaccuracies in DMSP data include: blurred images (Abrahams et al, 2018) and geo-location errors (Tuttle et al, 2013), so light is attributed to places other than where it is emitted; top-coding, where brightly-lit city centers get the same data values as low density, dimmer suburbs (Bluhm and Krause, 2018); and uncalibrated variation in DMSP sensor amplification and inter-satellite differences that impair comparability over time and space (Gibson et al, 2020). Also, DMSP data are increasingly out of date, as production of these data ended in 2013. Newer and better night lights data are available from April 2012 from the Visible Infrared Imaging Radiometer Suite (VIIRS) of instruments on the Suomi National Polar-orbiting Partnership (NPP) satellite platform. The VIIRS data have monthly frequency, with only a short lag (data are available to December 2019 at the time of writing in March 2020), giving an almost real-time measure of night-lit economic activity.

[2] Search made on 2 April, 2020. The count of 175 records excludes 60 records where the search terms capture papers that do not use satellite-detected night lights data.

The VIIRS data are far more precise than DMSP data, with 45-times greater spatial resolution (Elvidge et al, 2013) and have no blurring or geo-location errors.[3] The VIIRS data accurately measure the radiance of lights on earth, in a range of lighting conditions (covering almost seven orders of magnitude while DMSP covers less than two), while DMSP was designed to measure clouds for short-term weather forecasts. Thus, DMSP data show effects of unrecorded changes in sensor amplification (to keep brightness of cloud-tops constant over the lunar cycle), in terms of temporal inconsistency and top-coding. Inter-satellite differences also create inconsistency. The superiority of VIIRS has resulted in a rapid switch in the scientific literature; now almost twice as many articles per year publish using the VIIRS night lights data compared to those using the older and less accurate DMSP data, yet economists have continued to persist with DMSP data and largely ignore VIIRS (Gibson et al, 2020).

There are several barriers to the wider use of VIIRS night lights data by economists. The most widely used DMSP data are annual composites, that were cleaned by scientists at the National Oceanic and Atmospheric Administration (NOAA) to remove outliers created by ephemeral sources of light like aurora, fires, lightning, and boats. The equivalently-cleaned VIIRS annual composites are currently only available for 2015 and 2016. The monthly VIIRS data reported since April 2012 have not had the same cleaning and outlier removal, so there is no overlap with similarly processed DMSP data for a like-with-like comparison (Gibson et al, 2019). Yet without such a comparison it is harder to highlight flaws in the DMSP data. While the remote sensing literature has studies showing the superiority of VIIRS data (e.g. Chen and Nordhaus, 2015), there are no similar studies in economics journals.

To enable comparisons that illustrate measurement error properties of the DMSP data, this paper reports on a procedure to create cleaned annual estimates of night lights from the

[3] VIIRS data are allocated to grids, of about 0.45×0.30 kilometres for typical European latitudes. For DMSP, the grids are 0.93×0.60 kilometres but the underlying spatial resolution of the DMSP sensor is far coarser than is implied by this resampled grid.

monthly VIIRS data. This procedure provides overlapping annual estimates from both DMSP and VIIRS for 2013, to create a common testing ground. These data are used to predict GDP for almost 300 NUTS2 regions in Europe. The predictive power of VIIRS data is 80% higher than for DMSP data across a range of specifications. A Vuong (1989) likelihood ratio test suggests that models using the VIIRS data are closer to the truth. If the difference between (log) DMSP data and VIIRS data is used as an empirical estimate of the measurement error in DMSP data, a mean-reverting negative correlation of this error with true radiance is seen. Hence, coefficient estimates will be biased when DMSP night lights data are used on either the left-hand side or right-hand side of regression equations.[4]

Another implication of the mean-reverting error in DMSP night lights data is that spatial inequality will be understated if these data are used to measure patterns of economic activity. A Theil index calculated with DMSP data is less than one-half of what VIIRS data show for the NUTS2 regions, with the understatement of inequality especially in densely populated regions. An adjustment developed by Bluhm and Krause (2018) to deal with top-coding in DMSP data, which relies on a Pareto distribution for lights, has a modest effect but the adjusted DMSP data still greatly understate spatial inequality.

The research design used here relies on cross-sectional comparisons between the two sources of night lights data. This is because lights data are a far better proxy for differences in economic activity in the cross-section than for time-series changes in activity, so it is sensible to test these data in the context where they work best. For example, Goldblatt et al (2019) find changes in DMSP lights cannot predict changes in either the number of enterprises or in average household expenditures for communes in Vietnam (the third sub-national level), yet lights were highly predictive in the cross-section. Likewise, Nordhaus and Chen (2015) find

[4] See Gibson et al (2015) and Abay et al (2019) for full derivations of mean-reverting measurement error effects. Note that the main correction for measurement error bias that practitioners use – instrumental variables – is inconsistent if errors are mean-reverting (Black et al, 2000) and bounding estimates based on reverse regression are also likely to be ineffective (Gibson and Kim, 2010).

DMSP lights data are not a reliable proxy for time-series measures of output growth at either the country level or grid-cell level, yet they help estimate output per person cross-sectionally for countries with low quality GDP data. This superior performance in cross-sections also extends to VIIRS: variation in lights predicts 70% of the variation in state-level GDP in the U.S. but less than four percent of the variation in annual rates of change in GDP is predicted by annual changes in lights (Chen and Nordhaus, 2019; Gibson and Boe-Gibson, 2020).

Nevertheless, if time-series uses of night lights data are required, the procedure used here to clean the monthly data would enable a time-series to be constructed for 2012-2019. If a longer time-series is needed, the Pareto-adjusted DMSP data improve over the usual DMSP data and provide results that are closer to what VIIRS shows.[5] Thus, if needed, a researcher could obtain better night lights data, for longer, by splicing the cleaned VIIRS time-series with the time-series of Pareto-adjusted DMSP night lights data.

II. Sources of Mean-Reverting Errors in DMSP Night Lights Data

The measurement errors in DMSP data are mean reverting because blurred images attribute light to places from where it is not emitted and top-coding causes the differences in brightness between places to be understated. This matters because mean-reverting errors bias econometric estimates of regression coefficients, even if the error-ridden variable is on the left-hand side. Moreover, if there is a strong enough degree of mean-reversion in a right-hand side variable, the regression coefficient on that variable can be exaggerated rather than having the usual attenuation bias from random measurement error (Gibson et al, 2015).

The night time images that DMSP provides are inherently blurred, due to three flaws in the sensor and data management (Abrahams et al, 2018). First, away from the nadir of the

[5] Notwithstanding this improvement, Pareto-adjusted DMSP data still fall far short of the VIIRS data, in terms of their weaker relationship with GDP, understating spatial inequality, and missing key facilities like major ports (Gibson et al, 2019). Moreover, other sources of time-series inconsistency in DMSP data, due to inter-satellite differences and to unrecorded variation in sensor amplification over time, are not dealt with by the Pareto adjustment. Thus, threats to the validity of analyses of the DMSP time-series still remain (Gibson et al, 2020).

3000 kilometre (km) wide sweep of the sensor, the earth is viewed at an angle and the Field-of-View (FoV) expands (by four-fold at the sweep edge) but all light from the expanded FoV continues to be attributed to a far smaller pixel in the centre of the FoV. Second, the on-board computers cannot hold all the data, so pixels are aggregated to 5×5 blocks to save on memory storage. Third, random geo-location errors, with a mean of about 3 km, also spread recorded light away from its point of origin (Tuttle et al, 2013). Consequently, the ground footprint of the smoothed DMSP data is about 25 km^2 at the nadir and is even larger towards the edge of the sweep. In contrast, VIIRS maintains a constant 0.55 km^2 footprint over its full sweep, which is why remote sensing experts like Elvidge et al (2013) describe VIIRS as having at least 45-times greater spatial resolution than DMSP.

The 25 km^2 (or larger) ground footprint of the DMSP sensor is much larger than the 30 arc second (roughly 0.9×0.6 km at European latitudes) output grid onto which DMSP data are allocated. This may have created a confusion in economics that DMSP sensors can detect differences in lights for such small areas. For example, Baskaran et al (2015: 66) write about DMSP: "[t]hese images record average light output at the 30 arc second level, equivalent to about 1 km^2 at the equator." This is not correct, with the underlying spatial resolution of the sensor far coarser than the resolution of the grid used to output the resampled data. A related confusion is to attribute any spreading from the point of emission to where light is recorded in the DMSP data as due to environmental factors like snow and water (due to the reflection causing overglow), which should matter in only a few places.[6] In fact, blurring is an inherent feature of the DMSP data, and occurs in all environments.

Figure 1 illustrates blurring in DMSP data, using images for Oxford (and environs) in the 2015 VIIRS annual composite and the 2013 DMSP annual composite. The maps use the same scale and colour scheme. With VIIRS, it is clear that the nearby towns of Woodstock,

[6] For example, see the discussion in footnote 3 of Michalopoulos and Papaioannou (2014).

Abingdon, Didcot (where a power station increases the brightness) and Chilton are all distinct from Oxford, with unlit space lying between each town. Even Kidlington just to the north (where the London Oxford Airport is located) has unlit space separating it from Oxford. The VIIRS image also shows the two most brightly lit parts of Oxford are the MINI car factory at Cowley in east Oxford, and the area near Westgate Mall and Cornmarket street (the main shopping area). The brightness of these areas is about 160 nanoWatts per cm^2 per steradian.

In panel (b) of Figure 1, the blurring in the DMSP image of the same area is obvious. With DMSP it appears that a continuous lit area extends for almost 40 km from Woodstock through Oxford to Didcot and Chilton. Moreover, a lot of this area is given a Digital Number (DN) of 63 that DMSP allocates to the most brightly lit areas.[7] The apparently lit area is also much larger in the DMSP image. This exaggerated size is seen clearly for three small outer towns of Witney (population: 30,000), Wantage and Wallingford (population: 11,000 each) whose lit area in the DMSP image is 5-6 times larger than their actual lit area shown in the VIIRS image.[8] It also appears in the DMSP data that most of Oxfordshire is covered in light, with very little of the map in part (b) of Figure 1 showing the green colour for no light. Yet the reality is that much of Oxfordshire is unlit, as seen in panel (a). One impact of overstating lit area, through DMSP data wrongly attributing light to unlit hinterland areas, is to create a mean-reverting error.

Most uses of DMSP night lights in economics are at much larger scale than the areas shown in Figure 1, so it might be felt that the blurring issue is unimportant. The results for the NUTS2 regions shown below will allow this claim to be assessed, as this level of aggregation combines several counties into one unit (e.g. UKJ1 combines Oxfordshire with Berkshire and

[7] The DN comes from 6-bit quantization (2^6=64) and ranges from 0 (no lights) to 63 (brightest lights). The same DN value does not necessarily refer to the same brightness level in different years, due to the lack of calibration for DMSP sensors and due to inter-satellite differences (Doll, 2008).
[8] The exaggeration of lit area is a feature of DMSP data. Gibson et al (2020) show a 150% overstatement in estimated area of a very big city (Dar es Salaam), and up to 500% overstatement in area for smaller towns, while Abrahams et al (2018) find that DMSP data overstate city area by an average of 77% across 15 big cities.

Buckinghamshire). Moreover, a recent trend in economics is to use DMSP night lights data for ever smaller areas and so concern about blurring should have become more apparent, yet it remains largely ignored, as seen in the review by Gibson et al (2020). For example, the spatial units used by Heger and Neumayer (2019) are about one-tenth of the size of the area mapped in Figure 1, and those used by Lee (2018) are about one-hundredth of the size of Figure 1, yet the issue of blurring is ignored in these papers. Even when DMSP data are used for larger spatial units, such as at the national level, researchers always repeat the claim that the DMSP data have spatial resolution of about 1 km^2, and this apparent precision is likely to have given an unjustified air of confidence to their results.

The second source of mean-reverting error in the DMSP data is top-coding, which is due to three factors. First, the aim of DMSP was to measure clouds rather than to measure lights on earth, so the sensor amplification was turned up going into the dark part of the lunar cycle when cloud-tops are no longer visible in raw moonlight. Second, the sensor has only a low dynamic range, so when amplification is increased the images for brightly lit parts of the earth, such as central business districts, are saturated with light. Third, data storage limits meant that pixels were aggregated to 5×5 blocks to save on memory before the data were transmitted to earth, so the original 8-bit values for the so-called 'fine pixels' were divided by four and top-censored at 63, to give the 6-bit DN value widely used in economics. Globally, about six percent of pixels have top-coded DN values of 63, and, consequently, city centers often seem no brighter than lower density suburbs (Bluhm and Krause, 2018).[9]

Figure 2 illustrates top-coding in the DMSP data, using images for Inner and Outer London in the 2015 VIIRS annual composite and the 2013 DMSP annual composite. The most brightly lit part of London is Heathrow airport, whose radiance is 499 $nW/cm^2/sr$, which

[9] There also are radiance-calibrated DMSP lights data (for 1996, 1999, 2000, 2002, 2004, 2005 and 2010) from experiments where NOAA had the Air Force reduce amplification on a few nights to see what settings avoid DN values being top-coded in urban areas. However, these data rely on the pre-flight calibration of the sensor, rather than its actual (degraded) performance as it is exposed to dust and radiation over time, reducing their usefulness.

is over three times as bright as the most brightly lit part of Oxford in Figure 1(a). Some of the brightly lit areas of Inner London include Canary Wharf, Mayfair and Covent Garden, and the City of London; radiance in these areas is up to twice that recorded for the brightest parts of Oxford. Smaller, isolated, bright spots in panel (a) of Figure 2 include Wembley stadium, Twickenham, and Emirates stadium.[10] It is also clear that much of Outer London, especially to the south and northeast, is not brightly lit. Even in Inner London, large areas such as Hyde Park and The Regent's Park show almost no light output in the VIIRS image.

The DMSP data give a completely different picture of London, as seen in panel (b) of Figure 2. The entire city, including most of Outer London, appears to be an undifferentiated blob, with 77% of the pixels given the top DN value of 63, and 10% given a DN value of 62. In the DMSP image, Heathrow looks no brighter than its surrounds and other locations of concentrated economic activity, like Canary Wharf or the City of London, are also not identified.[11] Moreover, according to the DMSP data, the brightest areas of London are no brighter than the brightest areas of Oxford, when in fact they are 2-3 times as bright in the VIIRS data. It is evident that top-coding causes differences in brightness between places to be greatly understated, which is another source of mean-reverting errors.

III. From Monthly VIIRS Night Lights Data to Annual Estimates

The maps shown in Figures 1 and 2 rely on global annual composites created by NOAA scientists, that screen out ephemeral sources of light, such as from aurora, fires, and boats. Currently, the only annual composites for VIIRS are for 2015 and 2016, and so there is no overlap with the DMSP annual composites that ended in 2013. While monthly VIIRS data

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[10] The 2015 VIIRS image for London uses 2940 pixels, each having from 52 to 77 cloud-free nights (mean: 64) primarily in winter (due to solar glare in summer months). These sports stadiums will be repeatedly lit on winter nights, so even if the lights are not on every night, they still count as sources of non-ephemeral lights.

[11] This failure of the DMSP data to highlight intra-city heterogeneity is not restricted to London. Gibson et al (2019) show that 82% of Jakarta is given a DN value of 63 and 17% gets DN=62, while the major port that handles two-thirds of Indonesia's goods trade (and is the 22nd busiest port in the world ranked just ahead of the port of New York/New Jersey) cannot be distinguished from its surrounding area (yet VIIRS shows it clearly).

are filtered to omit pixel-nights affected by stray light and clouds, the remaining data are still affected by ephemeral sources of light such as aurora, fires and gas flares and so are not directly comparable to cleaned annual DMSP data (there are no monthly DMSP data).

One way to clean the monthly VIIRS data to improve comparability with the annual composites is to remove observations for any pixels that are recorded as having no permanent lights in the cleaned annual composites. In other words, if a pixel is recorded as having light in a monthly record from 2013 but shows up as unlit area in 2015 after the NOAA scientists have applied their algorithms to clean the annual composite, then a reasonable assumption is that the light recorded in the monthly file was ephemeral.[12] This same principle can extend to using the 2016 annual composite; a looser criteria for having non-ephemeral lights is that the pixel was classified as lit area in either the 2015 or the 2016 annual composite. This approach leverages off the earlier cleaning efforts of the NOAA scientists, by using a background noise mask derived from the annual composite(s), which is then applied to the monthly data.

One issue with implementing this procedure is that for typical European latitudes the VIIRS files for several months record no lights because the data have been filtered out due to the impact of stray light on long summer evenings. There is a clear north-to-south pattern in the map in Figure 3, with more northerly NUTS2 regions having only six months with data (January to March and October to December).[13] In contrast, regions in southern Europe have nine or more months with data, although only Cyprus has data for all 12 months. To ensure consistency over space, the VIIRS annual estimates that I create only use monthly data for January to March and October to December, even if other months have data available.

To test if this procedure for getting annual estimates from monthly VIIRS data yields a good proxy for the annual composites made by NOAA scientists, and therefore lets one

[12] There is a very weak, or even no, relationship between changes in local economic activity and changes in night lights (Chen and Nordhaus, 2019, Goldblatt et al, 2019, Gibson and Boe-Gibson, 2020) so a local economic downturn would not necessarily cause pixels in the area to switch from being lit to unlit.
[13] The one region in northern Norway with only five months of data is excluded from the analyses.

expand VIIRS annual data beyond 2015 and 2016 to allow like-with-like comparisons with DMSP annual composites in 2013, I use the following three regression specifications:

$$\ln(2015\,VIIRS\ Annual\ Composite)_i = \alpha + \beta\ln(sum\ of\ monthly\ lights)_i + \varepsilon_i \quad (1)$$

$$\ln(2015\,real\ GDP)_i = \alpha + \beta\ln(2015\,VIIRS\ Annual\ Composite)_i + \varepsilon_i \quad (2)$$

$$\ln(2015\,real\ GDP)_i = \alpha + \beta\ln(sum\ of\ monthly\ lights)_i + \varepsilon_i \quad (3)$$

In all three specifications, the *i* units are NUTS2 regions in Europe. While night lights data are typically used for places that have either missing or unreliable GDP, the focus on Europe is helpful here because reliable GDP data for NUTS2 regions give a benchmark for assessing the success of the various night lights data as a proxy for economic activity.

The annual composites appear to provide an effective mask to filter out ephemeral lights and other background noise in the monthly VIIRS data.[14] The results in the first three columns of Table 1 are for equation (1), with three different types of monthly lights used: unmasked (so simply the sum of all lights in a NUTS2 region across six months of the year); masked using the 2015 annual composite, so monthly lights coming from any pixel that was classified as unlit in the 2015 annual composite are excluded; and, using the combination of the 2015 and 2016 annual composites to mask out background noise in the monthly VIIRS data. If the unmasked data are used, the sum of monthly lights predicts lights in the annual composite with an adjusted-R^2 of 0.938 (or 0.956 if country dummy variables are included). In contrast, if either of the two masking approaches are used, the adjusted-R^2 is over 0.99, with or without country dummy variables. Additional support for using the sum of masked monthly lights as a proxy for the VIIRS annual composite comes from the elasticities of 1.0 that are estimated from the equation (1) regressions reported in Table 1.

Further evidence that the sum of masked monthly lights is a good proxy for the annual

[14] The VIIRS data are available from: https://eogdata.mines.edu/download_dnb_composites.html The annual composite is the “vcm-orm-ntl” product that, at the pixel level, excludes nights if images are affected by stray light or by clouds, has outliers due to ephemeral lights removed, and the background (non-lights) is set to zero.

composite comes from estimates of the relationship between annual lights and annual GDP at the NUTS2 level. If the VIIRS annual composite for 2015 is used to estimate equation (2), the elasticity is 0.929 and the adjusted-R^2 is 0.766 (if country dummies are not included the corresponding values are 0.666 and 0.427). The elasticity and the predictive power are much lower if the unmasked sum of monthly lights is used to estimate equation (3), with the adjusted-R^2 dropping by more than 10 percentage points. This suggests that unmasked monthly lights are not a good proxy for the VIIRS annual composite. In contrast, using the same monthly VIIRS data, but applying a mask to filter out ephemeral light and background noise for pixels that were classified as unlit in the annual composite gives results that are almost exactly the same as using the annual composite constructed by the NOAA scientists. In particular, the results in the last two columns of Table 1 are almost identical, in terms of the elasticities and the predictive power, to the results using the VIIRS annual composite.

IV. Night Lights, GDP and Measurement Error

The results in Table 1 provide support for the use of masked monthly VIIRS data to form an annual estimate that is comparable to the annual composites constructed by NOAA. Consequently, a like-with-like test of the DMSP night lights data can be carried out, using the constructed VIIRS annual estimate for 2013 as the benchmark. Three main variables are used for this test: the 2013 VIIRS annual estimate discussed above; the DMSP annual composite from satellite F18 for 2013;[15] and, real GDP in terms of purchasing power standards.[16]

This test is a cross-sectional comparison and so it does not inform about time-series measurement errors in the DMSP data. However, it does test the lights data in the context in which they work best. Also of note is that it is an equation like equation (3) that is estimated, with lights on the right-hand side and GDP on the left-hand side. This setup is not meant to

[15] These data can be downloaded from https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html
[16] These data are available from Eurostat: https://ec.europa.eu/eurostat/web/products-datasets/-/tgs00004

imply that lights cause GDP because as a production function it should be the other way around. Instead, the aim is to see how well various night lights data proxy for GDP. Most uses of night lights data in economics are to proxy for local economic activity in places where GDP data are either not reported with sufficient spatial detail or are reported but considered unreliable. Given that the aim of most studies using night lights data is to estimate the impact of some treatment, such as a natural disaster or sanctions, on local economic activity, what is implied when lights are used as the outcome measure is that underlying the reported effects is a relationship like: $(\partial GDP/\partial lights) \cdot (\partial lights/\partial treatment)$ because we are generally not interested in lights, *per se*. Thus, the usually unobserved relationship with local GDP on the left and lights data on the right is of interest for interpreting the results from this literature, especially if lights are a poor proxy for local GDP.

The results in Table 2 are based on a double-log specification to examine how well GDP is predicted by the sum of lights (either DMSP or VIIRS) at the NUTS2 level. One set of results includes country dummy variables, to allow for national-level factors that shift the level of GDP in a region conditional on luminosity. If the VIIRS data are used to predict GDP, the results in column (1) show that the adjusted-R^2 is 0.757 and the elasticity is 0.93 (or 0.434 and 0.69 if country dummy variables are omitted). In contrast, if the DMSP data are used, the results in column (2) show that the adjusted-R^2 is just 0.303 (or 0.460 with country dummy variables) and the elasticity is 0.57 (or 0.63 with country dummies). Thus, predictive power is 43-65% higher with VIIRS than with the widely used DMSP night lights data.

The NUTS2 regions vary widely in population, from 30,000 in the least populous to 14 million in the most populous (median: 1.5 million). These population differences also flow through into density differences, as population and area of NUTS2 regions are uncorrelated. Given that GDP is concentrated in high density areas, giving equal weight to all regions may be unwarranted, so the results in columns (4) and (5) are population-weighted. In these results the superior predictive performance of the VIIRS data is even more apparent; the adjusted-R^2 of the models using the DMSP data falls while there is almost no change in the predictive power for the regressions using the VIIRS data. One reason why weighting may affect the predictive power of DMSP data is that the DMSP sensor attenuates the differences between brightly lit big cities and smaller towns (as seen if Figures 1 and 2 for London and Oxford). So if all regions are treated as equals in a regression, the flaws in DMSP data are less exposed than they are when allowance is made for the fact that much of the population and economic activity is concentrated in a few regions. In contrast, more accurate data like VIIRS that show the true extent of luminosity differences between places do not produce results that are very sensitive to weighting by population.

Across the four sets of results in columns (1), (2), (4) and (5), using the VIIRS data to predict regional GDP gives 80% higher predictive power than using DMSP data, on average. Another way to compare between models using the two sources of night lights data is to use Vuong's (1989) likelihood ratio test that relies on the Kullback-Leibler Information Criterion (KLIC). Intuitively, the KLIC is the log-likelihood function under the hypothesis of the true model minus the log-likelihood function for the (potentially misspecified) model under the assumption of the true model. A model is better than a competitor if it is closer to the truth under the KLIC (Greene, 2012, p.535). For all four models, the Vuong test indicates that a model using VIIRS data is significantly closer to the truth than a model using DMSP data.

The last set of results in Table 2, reported in columns (3) and (6), use Pareto-adjusted DMSP data for 2013, developed by Bluhm and Krause (2018) and made available at their website: http://lightinequality.com/top-lights.html. To form these adjusted data, Bluhm and Krause assume that lights follow a Pareto distribution, and use this to replace the top-coded DN=63 values with higher DN values. This Pareto adjustment does improve the performance of DMSP data in predicting regional GDP, raising the adjusted-R^2 by an average of about

21 points compared to what was estimated using the original DMSP data. However, it is still the case that the VIIRS data provide greater predictive power, with the adjusted-R^2 values being up to 20% higher than what the Pareto-adjusted data give. The Vuong tests also show that models using VIIRS data are significantly closer to the truth than those using Pareto-adjusted DMSP data (for specifications that include country dummy variables).[17] However, any research that requires splicing the VIIRS time-series with the DMSP time-series would benefit from using the Pareto-adjusted DMSP data, which provide elasticities that are much closer to those coming from VIIRS data, especially in the population-weighted models.

The result in Table 2 that DMSP data are less successful at predicting regional GDP, in a like-with-like comparison using annual estimates for 2013, suggests that measurement errors in the DMSP data are having an impact. These errors can be empirically studied, if the VIIRS data are treated as the truth, which is implied by the Vuong test results. If the (log) sum of masked monthly VIIRS lights is subtracted from the sum of the DMSP DN values at NUTS2 level (these are two of the right-hand side variables used in Table 2) the differences are negatively correlated with the true radiance values (as measured by VIIRS). This same pattern is found in several other contexts and is referred to as *mean-reverting error* (see Abay, 2019 for a compilation of estimates of the mean-reverting error parameter).

More formally, consider the model: $y = \alpha + \beta x + u$, for an outcome variable y, an independent variable x, response coefficient β, and with a pure random error, u. The outcome variable has an observed value y^* that is related to the true value by:

$$y^* = \theta + \lambda y + v \tag{4}$$

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

[17] If Figure 2(a) for London is compared with the London map of Bluhm and Krause (2018) that is based on their Pareto-adjusted data, it is evident that the Pareto adjustment is not able to unmask key economic features, like Heathrow airport, that have been blurred by the DMSP sensor. So despite the improved results in predicting regional GDP there are still remaining flaws in these adjusted DMSP data.

true value. In contrast, if measurement errors are mean-reverting, $0 < \lambda < 1$. The estimator of the response coefficient if the error-ridden dependent variable is used is:

$$\beta_{y^*x} = \frac{cov(y^*,x)}{var(x)} = \frac{cov(\lambda\alpha+\lambda\beta x+\lambda u-v,x)}{var(x)} = \lambda\beta \tag{5}$$

Equation (5) provides a motivation for forming a point estimate, $\hat{\lambda}$ that can help to assess the extent to which published results using DMSP night lights as the left-hand side variable will have reported regression coefficients that have been attenuated.

For completeness, note that in the less common case where DMSP data are the right-hand side variable (and the setup for the error-ridden right-hand side variable is the same as in equation (4) and the outcome variable is measured without error), then it can be shown (e.g. Gibson et al, 2015) that the estimator of the response coefficient becomes:

$$\beta_{yx^*} = \frac{cov(y,x^*)}{var(x^*)} = \beta\frac{\lambda\sigma_x^2}{\lambda^2\sigma_x^2+\sigma_v^2} \tag{6}$$

For the special case of classical measurement error, with $\lambda = 1$, equation (6) simply gives the usual result, that the attenuation of the estimated response coefficient will be in proportion to the reliability ratio of the mis-measured right-hand side variable. However, for a sufficiently strong degree of mean reversion, the smaller first term in the denominator due to multiplying by λ^2 (for $0<\lambda<1$) may outweigh the effect of adding the variance of the random noise term (σ_v^2), and in that case the denominator of equation (6) becomes smaller than the numerator, and the regression coefficient will be exaggerated rather than attenuated.

It is likely that regression models with DMSP night lights data as their left-hand side variable have response coefficients that are attenuated by at least one-quarter. This claim is based on estimates of $\hat{\lambda}$ that range from 0.61 to 0.85, and average 0.73, and are all statistically significantly less than the value of 1.0 needed for the classical measurement error that does not bias coefficients when the error-ridden variable is on the left-hand side (Table 3). These estimates are based on equation (4) and relate only to cross-sectional use of night lights data.

There are additional time-series errors, discussed in Gibson et al (2020), that may further attenuate regression coefficients when DMSP data are on the left-hand side.[18]

The mean-reverting measurement errors in cross-sections of DMSP data have two potential sources: blurred images that attribute light to places from where it is not emitted and top-coding that attenuates the differences in brightness between places. The Pareto-adjusted DMSP data are meant to deal with the top-coding issue so remaining measurement error in these data should be due to the blurring that spreads light into places where it is not emitted. If the Pareto-adjusted data are treated as the error-ridden variable, and equation (4) is re-estimated, the estimates of $\hat{\lambda}$ range from 0.76 to 0.91, and average 0.83 (Table 3). All of the $\hat{\lambda}$ estimates are statistically significantly less than one, so even with the Pareto adjustment there is still mean-reverting error in the DMSP data. Given the results with and without the Pareto adjustment, it seems that the top-coding problem is causing a bit over one-third of the mean-reverting measurement error in the DMSP data, with blurring being the larger problem.

V. Night Lights and Spatial Inequality

The mean-reverting measurement errors in DMSP data, whose characteristics are described in Table 3, may distort a range of empirical economic analyses and should not just be thought of as a source of biased regression coefficients. As seen in Figures 1 and 2, the DMSP night lights data greatly understate spatial differences in night-lit economic activity. Many national, sub-national, and supra-national institutions have concerns about spatial inequality. Such concerns are prominent in Europe, with public transfers to sub-national regions being a key feature of the European Union. For example, Cohesion Funds are the second largest budget item after agricultural payments (which are also a form of regional

[18] For situations where the DMSP data are on the right-hand side, the estimates of λ are not so close to zero as to cause exaggerated regression coefficients (based on equation (6)). One indicator of such strong mean-reversion is that the variance of the error-ridden variable is smaller than the variance of the error-free variable. The DMSP data have a larger variance than the VIIRS data (scaling by their different means, given their different units).

policy), and these funds aim to promote a balanced development between regions in Europe. While spatial inequality in Europe can be studied with GDP data at the NUTS2 level, many other countries lack reliable sub-national GDP data and so DMSP night lights data have been used to study regional inequality (e.g., Lessmann and Seidel, 2017).

In line with expectations formed by looking at the London and Oxford maps, spatial inequality is considerably understated when using the DMSP data (Table 4). Across all of the NUTS2 regions, the Theil index calculated with DMSP data is less than one-half of what the VIIRS data show for the same year (0.26 versus 0.54). The understatement of spatial inequality is less pronounced with the Gini coefficient (0.40 versus 0.51) because the Gini is less sensitive to differences at the top of the distribution than is the Theil index.

Another way to show that the mean-reverting errors in DMSP data matter especially for more brightly lit regions with greater density of economic activity or population (which shows up as the Theil being more sensitive than the Gini to using DMSP rather than VIIRS) is to divide regions into two groups, using the median population density as the threshold. The results in Table 4 show that it is especially for high density regions that DMSP data understate spatial inequality; in these regions the Theil index calculated with the VIIRS data is 3.6 times as high as what is calculated with the DMSP data (and with the Gini index it is 1.7 times as high). In contrast, in low density regions, using VIIRS gives a Theil index just 1.2 times as high as what DMSP shows (and 1.1 times as high using the Gini).

The Pareto-adjusted DMSP data provided by Bluhm and Krause (2018) are designed to correct top-coding so it might be expected that these data would yield inequality statistics that are much more like what VIIRS data show. In fact, using the Pareto-adjusted data closes only a fraction of the gap in inequality measures, in terms of what is estimated from VIIRS data compared to what is estimated from DMSP data. Specifically, if the Pareto-adjusted data are used, one-third of the VIIRS-DMSP gap is closed when using the Theil index, and 40% of the gap is closed when using the Gini coefficient. Unexpectedly, using the Pareto-adjusted DMSP data closes even less of the DMSP-VIIRS inequality gap in more densely populated regions, which are exactly the places where correcting for top-coding of night lights data should do most good. Specifically, just 29% of the VIIRS-DMSP gap is closed for the Theil index and 36% of the gap is closed for the Gini index, when using the Pareto-adjusted data. Another concern with these Pareto-adjusted data is that they show no difference in spatial inequality between high density and low density regions, even as the VIIRS data show that spatial inequality is twice as high (using the Theil index, or almost one-third higher, using the Gini) in the more densely populated regions compared to the sparsely populated ones. So although the Pareto-adjusted data are helpful in giving a better fitting equation for predicting regional GDP, they do not seem to be very helpful for measuring spatial inequality.

VI. Conclusions

Applied economists have been busy in the last few years using satellite-detected night lights data to study many research questions. Almost all of these studies use data from the Defense Meteorological Satellite Program, which was set up to observe clouds for short-term weather forecasts rather than to observe lights on earth for economists. These DMSP data are flawed by blurring and top-coding, due to intrinsic features of the DMSP sensors and data management. While some economics studies using DMSP data acknowledge that these data may provide a noisy measure of true radiance (e.g. Henderson et al, 2012), the fact that the measurement errors are mean-reverting, and thus will cause econometric bias even when lights data are on the left-hand side, has not been highlighted. These mean-reverting errors also cause spatial inequality to be greatly understated.

Even while applied economists have increasingly used the flawed DMSP data, newer and better VIIRS data on night lights are available for the last eight years. One contribution of the current paper is to provide a procedure for practitioners to process the monthly VIIRS data into annual estimates that are comparable to cleaned annual composites produced by NOAA scientists. Such a procedure is needed because, to date, the cleaned annual composites have not been for an overlapping year with both DMSP data and VIIRS data. This lack of overlap has prevented a systematic comparison of the two data sources on night-time lights. With these newly processed VIIRS data, that overlap with DMSP data in 2013, I am able to establish four facts about satellite-detected night lights data:

- The VIIRS data are a much better proxy for sub-national GDP, with predictive power about 80% higher than for the DMSP data in a cross-section of NUTS2 regions
- Mean-reverting measurement errors in DMSP data will cause regression coefficients to be attenuated by at least one-quarter if DMSP night-lights are on the left-hand side
- The mean-reverting errors are due to top-coding and blurring, so dealing with just one problem, as with the Pareto-adjustment for top-coding, still yields error-ridden data that will distort reality (e.g. by greatly understating spatial inequality)
- Nevertheless, if a time-series based on VIIRS data needs to extend back before 2012, the Pareto-adjusted DMSP data are likely to provide a better proxy for sub-national GDP than what is provided by the usual DMSP data.

These findings provide a basis for practitioners to switch to using better night lights data, which are available for longer because the VIIRS time-series can extend beyond 2013.

In addition to these forward-looking conclusions, the findings reported in this paper also have a backward-looking implication. Many applied economics papers published using DMSP night lights data highlight the supposed precision of these data, in terms of being able to detect differences in light for areas as small as 1 km^2 where these differences are meant to indicate, at fine scale, the local economic effects of the various interventions studied. Some of the confidence in these results is likely to be misplaced because DMSP data are revealed here to be far cruder measures than is usually admitted. For example, visual comparisons in this paper show that DMSP data make a big city like London look no brighter than Oxford, make a fairly rural county like Oxfordshire seem to be almost entirely covered in lights, and cannot distinguish the most brightly lit feature in all of England – Heathrow airport – from the surrounding area. These flaws, and others, are likely repeated in all of the contexts where DMSP data have been used, and so there may need to be a reappraisal of some economics results based on DMSP night lights data.

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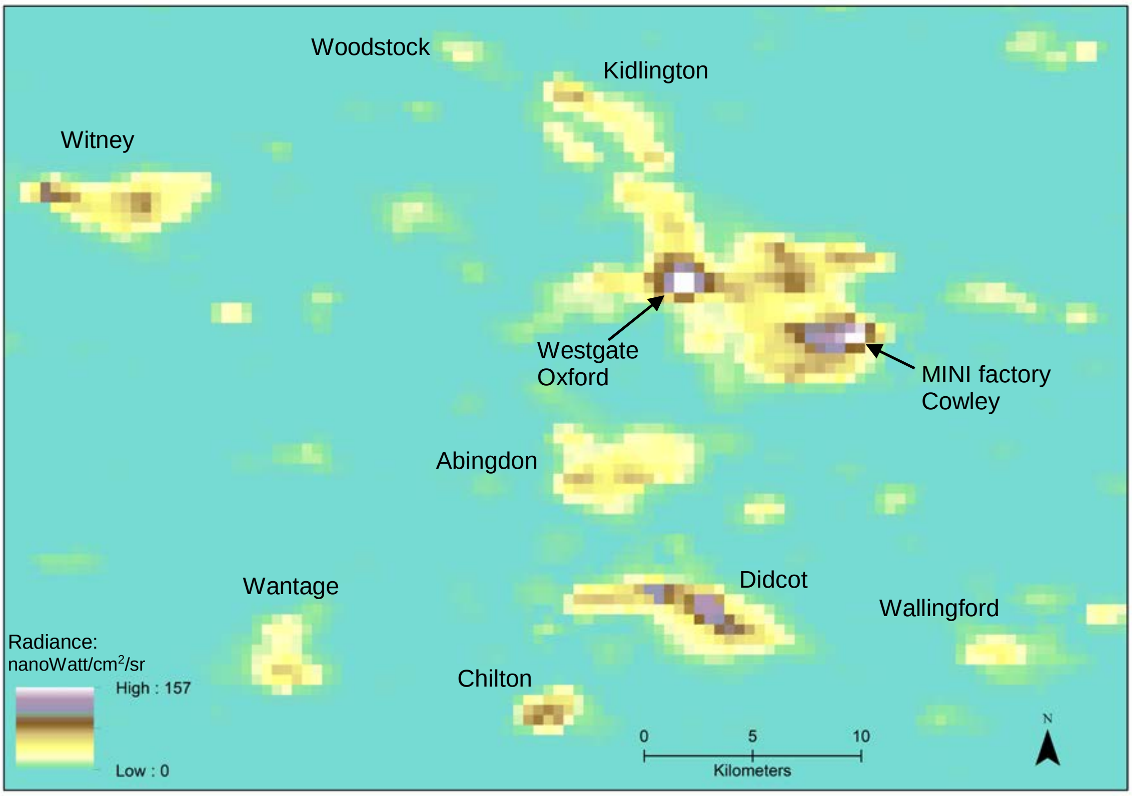
Figure 1: Illustrating Blurring in DMSP Night Lights: Oxford and Environs

(a) VIIRS Outlier Removed Annual Composite, 2015



(b) DMSP Stable Lights Annual Composite, 2013

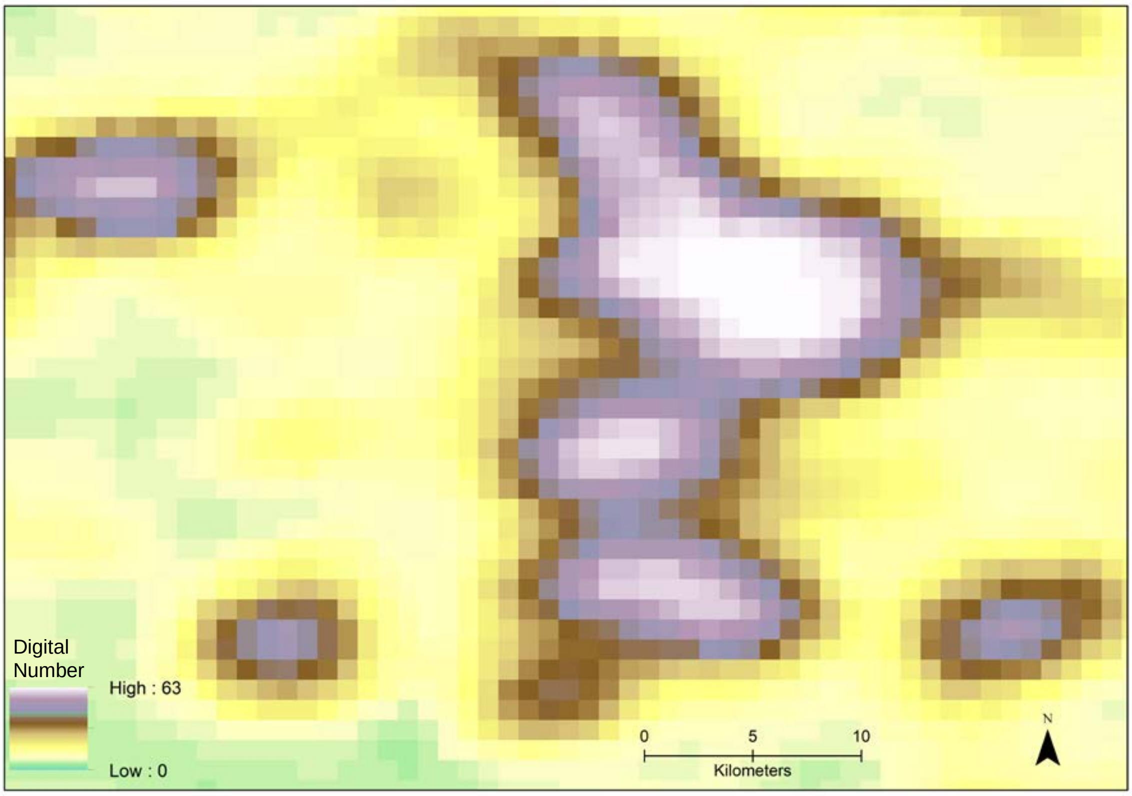
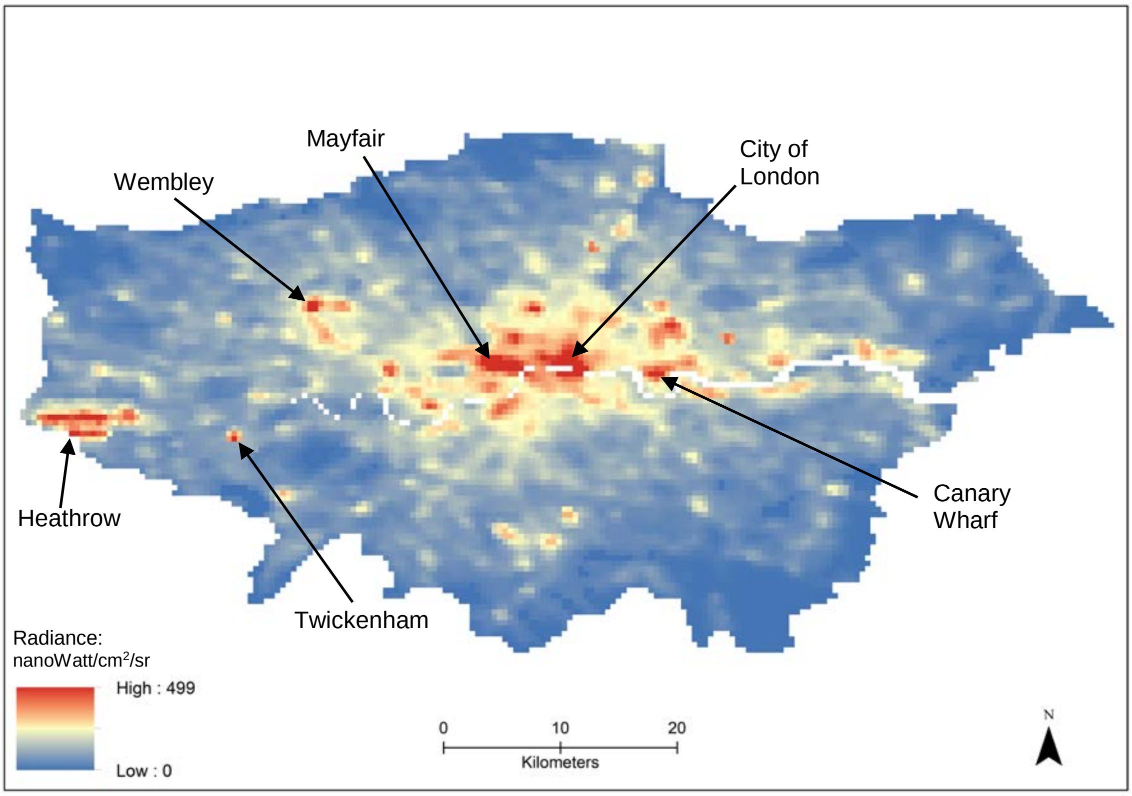


Figure 2: Illustrating Top-Coding in DMSP Night Lights: Inner and Outer London

(a) VIIRS Outlier Removed Annual Composite, 2015



(b) DMSP Stable Lights Annual Composite, 2013

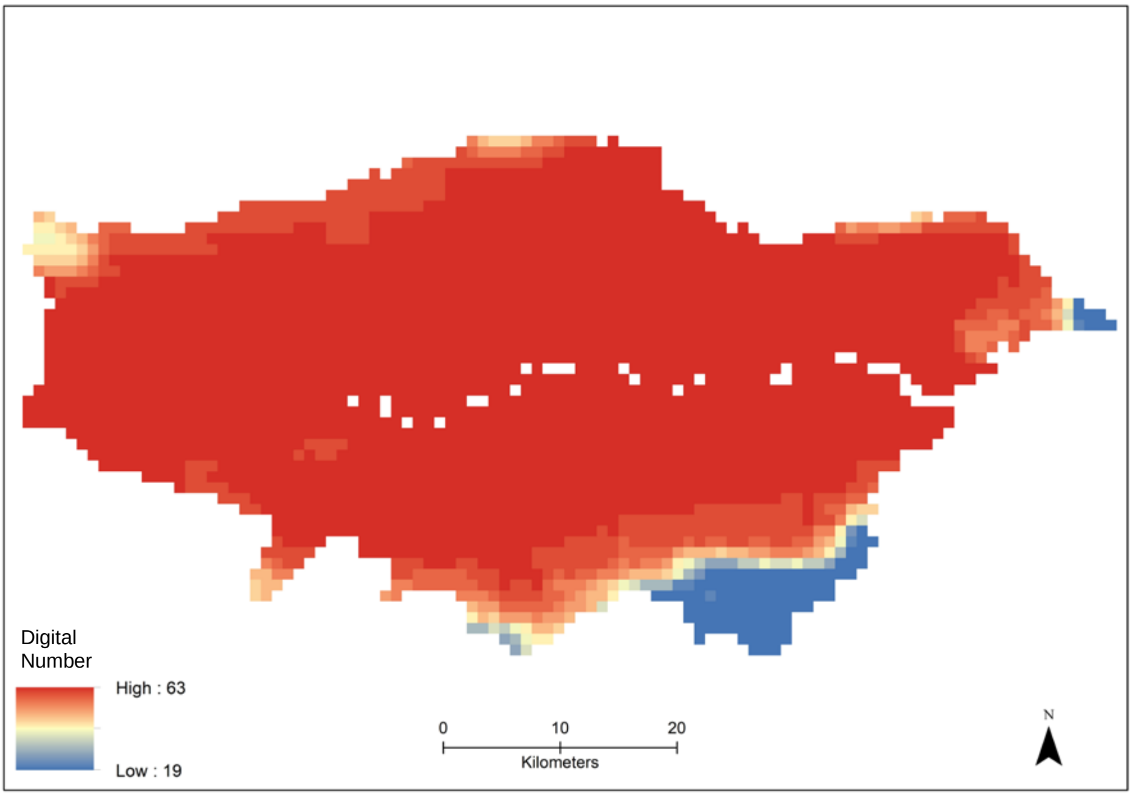


Figure 3: Number of Months With VIIRS Data, 2013: Europe NUTS2 Regions

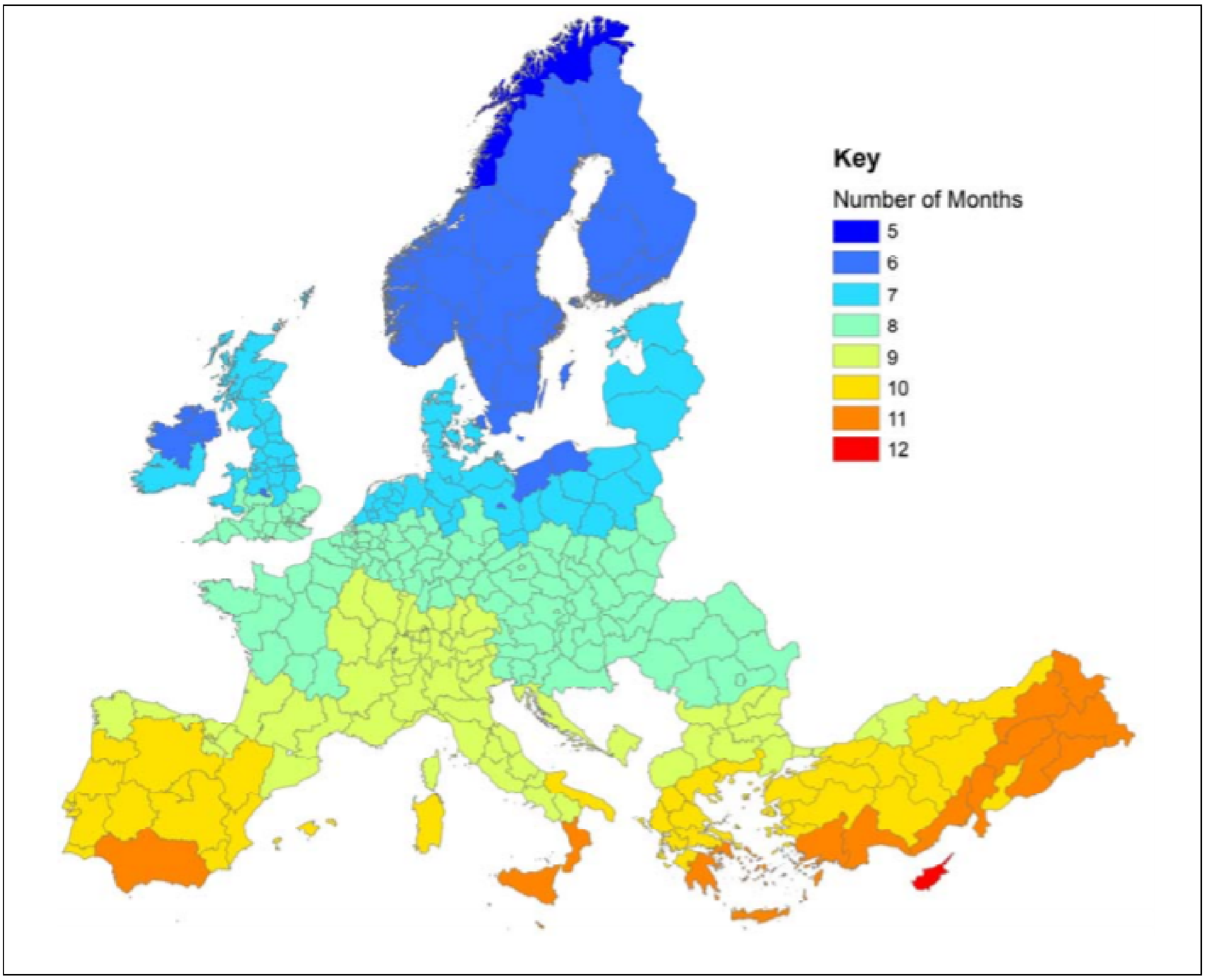


Table 1: Using Masked Monthly Lights to Create Annual Estimates Closely Approximates VIIRS Outlier-removed Annual Composites

	ln (2015 VIIRS annual composite)			ln (2015 GDP, real Purchasing Power Standards)			
	Panel A: Excluding Country Dummy Variables						
ln (lights), outlier-removed annual composite				0.666 (0.047)			
ln (lights), sum of monthly, no pixels masked	0.986 (0.014)				0.590 (0.052)		
ln (lights), sum of monthly, for pixels that are lit in the 2015 outlier-removed annual composite		1.004 (0.005)				0.670 (0.047)	
ln (lights), sum of monthly, for pixels that are lit in the 2015 or 2016 outlier-removed annual composites			1.013 (0.005)				0.683 (0.048)
Constant	-1.880 (0.194)	-1.816 (0.061)	-1.988 (0.070)	2.905 (0.534)	2.548 (0.695)	1.675 (0.622)	1.473 (0.627)
Adjusted R^2	0.938	0.993	0.992	0.427	0.324	0.426	0.433
	Panel B: Including Country Dummy Variables						
ln (lights), outlier-removed annual composite				0.929 (0.037)			
ln (lights), sum of monthly, no pixels masked	1.014 (0.016)				0.855 (0.048)		
ln (lights), sum of monthly, for pixels that are lit in the 2015 outlier-removed annual composite		1.001 (0.005)				0.922 (0.038)	
ln (lights), sum of monthly, for pixels that are lit in the 2015 or 2016 outlier-removed annual composites			1.007 (0.006)				0.927 (0.039)
Constant	-2.373 (0.210)	-1.774 (0.065)	-1.900 (0.075)	0.782 (0.408)	-0.345 (0.626)	-0.774 (0.485)	-0.880 (0.492)
Adjusted R^2	0.956	0.995	0.994	0.766	0.636	0.752	0.750
Observations	311	311	311	269	269	269	269

Notes: The dependent variables in the first three columns are log lights for the 2015 VIIRS annual composite (cloud mask, outlier removed and non-lit background set to zero) at the NUTS2 region level, and for the last four columns are log real GDP (in purchasing power standard terms) in 2015. The sum of monthly lights uses images for January to March and October to December, as images for other months of the year are affected by glare from evening sunlight. Robust standard errors in parentheses.

Table 2: Estimated Relationships Between Night Lights and Real GDP in 2013 for NUTS2 Regions

	Unweighted			Population Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Excluding Country Dummy Variables					
ln (sum of VIIRS masked monthly lights)	0.688			0.690		
	(0.055)			(0.069)		
ln (sum DMSP annual lights)		0.570			0.564	
		(0.078)			(0.099)	
ln (sum Pareto-adjusted DMSP annual lights)			0.738			0.811
			(0.059)			(0.080)
Constant	1.386	3.444	1.306	1.495	3.880	0.642
	(0.728)	(0.956)	(0.732)	(0.910)	(1.244)	(0.984)
Adjusted R^2	0.434	0.303	0.463	0.454	0.223	0.443
Vuong test (p-value)	----	0.003	0.347	----	0.000	0.402
	Panel B: Including Country Dummy Variables					
ln (sum of VIIRS masked monthly lights)	0.932			1.065		
	(0.050)			(0.112)		
ln (sum DMSP annual lights)		0.626			0.560	
		(0.079)			(0.125)	
ln (sum Pareto-adjusted DMSP annual lights)			0.841			1.056
			(0.062)			(0.131)
Adjusted R^2	0.757	0.460	0.646	0.726	0.328	0.606
Vuong test (p-value)	----	0.000	0.000	----	0.000	0.000

Notes: Robust standard errors in ( ), N=268 NUTS2 regions. Models in panel B include 29 country dummy variables (so the intercept is not reported). The dependent variable is log real GDP (in purchasing power standards) in 2013. The VIIRS lights are based on the sum of six months (January to March and October to December) using the combined 2015 and 2016 VIIRS annual composites as a mask to filter out ephemeral lights and background noise. The Vuong test establishes which of two models is closer to the truth. A p-value less than 0.05 indicates statistically significant evidence in favour of the truth of the null model (the model using VIIRS data, in this case), rather than the truth of the competitor model.

Table 3: Estimates of the Mean-Reverting Measurement Error Parameter in DMSP and Pareto-Adjusted DMSP Data

	Unweighted		Population Weighted	
	DMSP	Pareto-adjusted	DMSP	Pareto-adjusted
	Panel A: Excluding Country Dummy Variables			
Mean-reverting error parameter, $\hat{\lambda}$	0.790	0.845	0.651	0.758
	(0.060)	(0.046)	(0.050)	(0.033)
t-test for non-classical errors $H_0: \lambda = 1, H_1: \lambda < 1$	3.50***	3.40***	7.03***	7.26***
	Panel B: Including Country Dummy Variables			
Mean-reverting error parameter, $\hat{\lambda}$	0.845	0.910	0.610	0.782
	(0.085)	(0.063)	(0.062)	(0.048)
t-test for non-classical errors $H_0: \lambda = 1, H_1: \lambda < 1$	1.82**	1.42*	6.28***	4.55***

Notes: Coefficients are from estimating equation (4) with VIIRS data as the right-hand side variable and the left-hand side variable is either DMSP or Pareto-adjusted DMSP data. Robust standard errors in ( ), ***, **, * denote statistical significance at 1%, 5% and 10% level. *N*=269 NUTS2 regions. Models in panel B include 29 country dummy variables.

Table 4: DMSP Data on Night Lights Considerably Understate Spatial Inequality, Even After Pareto Adjustment for Top-Coding

	Gini coefficient			Theil Index		
	All regions	Low density	High density	All regions	Low density	High density
DMSP ('stable lights')	0.397	0.306	0.245	0.261	0.146	0.100
	(0.020)	(0.022)	(0.018)	(0.027)	(0.021)	(0.013)
DMSP (Pareto-adjusted	0.444	0.324	0.307	0.355	0.164	0.175
for top-coding)	(0.023)	(0.024)	(0.021)	(0.036)	(0.025)	(0.023)
VIIRS Day-Night Band	0.508	0.333	0.417	0.536	0.178	0.356
	(0.024)	(0.025)	(0.031)	(0.069)	(0.027)	(0.073)
Number of observations	310	155	155	310	155	155

Notes: Bootstrapped standard errors in ( ) from 1000 replications. Inequality statistics are based on the share of total lights (in 2013) and of total area from each NUTS2 region.