Global inequality remotely sensed

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Economic inequality is notoriously difficult to quantify as reliable data on household incomes are missing for most of the world. Here, we show that a proxy for inequality based on remotely sensed nighttime light data may help fill this gap. Individual households cannot be remotely sensed. However, as households tend to segregate into richer and poorer neighborhoods, the correlation between light emission and economic thriving shown in earlier studies suggests that spatial variance of remotely sensed light per person might carry a signal of economic inequality. To test this hypothesis, we quantified Gini coefficients of the spatial variation in average nighttime light emitted per person. We found a significant relationship between the resulting light-based inequality indicator and existing estimates of net income inequality. This correlation between light-based Gini coefficients and traditional estimates exists not only across countries, but also on a smaller spatial scale comparing the 50 states within the United States. The remotely sensed character makes it possible to produce high-resolution global maps of estimated inequality. The inequality proxy is entirely independent from traditional estimates as it is based on observed light emission rather than self-reported household incomes. Both are imperfect estimates of true inequality. However, their independent nature implies that the light-based proxy could be used to constrain uncertainty in traditional estimates. More importantly, the light-based Gini maps may provide an estimate of inequality where previously no data were available at all.

inequality | remote sensing | nighttime light

Over the past decades, there has been a transition from theoretical to data-driven inequality research (1). However, progress is limited by a lack of data on economic prosperity at the household level (2) as well as the absence of consensus on ways of measuring economic inequality (3, 4). Practical constraints include limited coverage, incomparability at population subscales, dependence on misreported income surveys, and low-quality data collection in developing economies (5–7). Furthermore, since traditional inequality measures are not georeferenced at different geographic scales, they cannot be used in subregional studies. Thus, despite broad interest in inequality, empirical approaches remain contentious (8). Since the late twentieth century, initiatives like the World Income Inequality Database, the Luxembourg Income Study Database, and the World Wealth and Income Database have partly filled this lacuna. However, these datasets still suffer from large regional variations in coverage, data quality, and lack of compatibility concerning collection methodologies (9, 10). The vast majority of publications in inequality research are based on data from North America and Western Europe (11). As a result, while inequality in the developed world is relatively well documented (12–14), our knowledge about inequality in the developing world is limited by paucity, poor quality, uncertainty, and incomparability of data (15, 16). This implies that we know the least about areas where inequality perhaps presents the most serious developmental policy challenge.

Here, we suggest a way to use remotely sensed nighttime light (NTL) for filling this gap. NTL is a globally uniform metric reflecting the nocturnal anthropogenic use of lights (17, 18). Almost all economic activities occurring in postdaylight hours, be it consumption or production, require the use of artificial lights, an assertion corroborated by studies showing NTL to be highly related with indicators of economic activity (19–22).

Approach

In general, as income rises, the emitted light per person increases due to factors such as bigger, brighter-lit houses and well-illuminated neighborhoods in richer areas (23). While the link between NTL and economic thriving is well established, the idea to use NTL for detecting economic inequality is relatively new. We reason that, if households with different incomes live more or less segregated across landscapes (24), spatial variation in per capita NTL should to a certain extent reflect variance in per capita income. The approach is straightforward. We calculate average light intensity per person (LPP) for each grid cell, dividing available NTL data by population density estimates (*Materials and Methods*). We then characterize inequality in the distribution of LPP across sets of grid cells by computing Gini coefficients for each set. This way, we compute Gini coefficients for nations as well as for a finer subnational level. We exclude areas that have no residential population (such as industrial zones) or no detectable NTLs (such as deserts, forests).

Our approach is fundamentally different from the traditional way of characterizing economic inequality, as we estimate inequality between spatial units rather than between households. Since the spatial resolution of the remotely sensed data is too coarse to detect individual households, our approach can only work if households of different wealth are not homogeneously distributed across neighborhoods and regions. While indeed there is a well-established tendency for spatial segregation in residential housing (25), it raises the a priori question of when spatial variation in lights may reasonably be expected to reflect household variation in economic prosperity. To explore how segregation and sampling resolution should be expected to affect our remotely sensed indicators, we used an adapted version of the Schelling segregation model (26) to generate different levels of spatial segregation in

Significance

Reliable data on economic inequality are largely limited to North America and Western Europe. As a result, we know the least about areas where inequality presents the most serious developmental policy challenge. We demonstrate that spatial variation in night-light emitted per person can reflect the distribution of income. This allows us to map global patterns and trends in economic inequality using remote sensing.

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income and subsequently sampled the results at different resolutions to mimic remote sensing (*SI Appendix*).

Results

To explore empirically if our remotely sensed proxy may indeed capture a signal of economic inequality, we examined the relationship between our light-based indicator and traditional estimates of income inequality based on self-reported household incomes.

Inequality across Nations. Existing estimates of national net income inequalities across the globe do indeed correlate to our light-based proxy (Fig. 1*C*) (Pearson's $r = 0.44$). A linear model controlling for population count and gross domestic product (GDP) as covariates explains 73% of the variation in net income inequalities (Table 1 shows model specification, coefficient estimates, and comparison across alternate specifications for robustness). We also compared a model with only our covariates (population and GDP) with the model with light Gini added. The latter performed significantly better (*SI Appendix*).

There is no one-to-one relationship between our light-based Gini coefficients and the available traditional estimates, and the average global light-based Gini of 0.58 is higher than the average net income-based Gini of 0.38. Nonetheless, qualitative global patterns in both estimates are comparable. For instance, broadly speaking, high-inequality hot spots like Russia, China, Southeast Asia, and most of Africa and South America come out as prominent by both light and income Gini estimates, while Western Europe and Canada feature consistently as regions of lower inequality (Fig. 1 *A* and *B*).

Grouping income- and light-based inequality and seeing them by income groups (using World Bank classification of the world's economies) and regions (continents) globally confirm the image that the light-based inequality estimators are indeed related to income inequality. Light-based Gini is significantly lower ($P < 0.01$, Welch two-sample t test) for high-income countries than for low- and middle-income countries (Fig. 2*A*), consistent with the pattern for income Gini (Fig. 2*B*). Looking at regions, the light-based Gini of Europe is the lowest ($P < 0.01$, Welch two-sample t test) among all continents followed by Asia, the Americas, Oceania, and Africa (Fig. 2*C*). Again, this is in line with the pattern for income Gini, although here, the Americas emerged as the most unequal continent (Fig. 2*D*).

Inequality across US States. Within the United States, we were able to zoom in to somewhat finer scales by making use of state-level

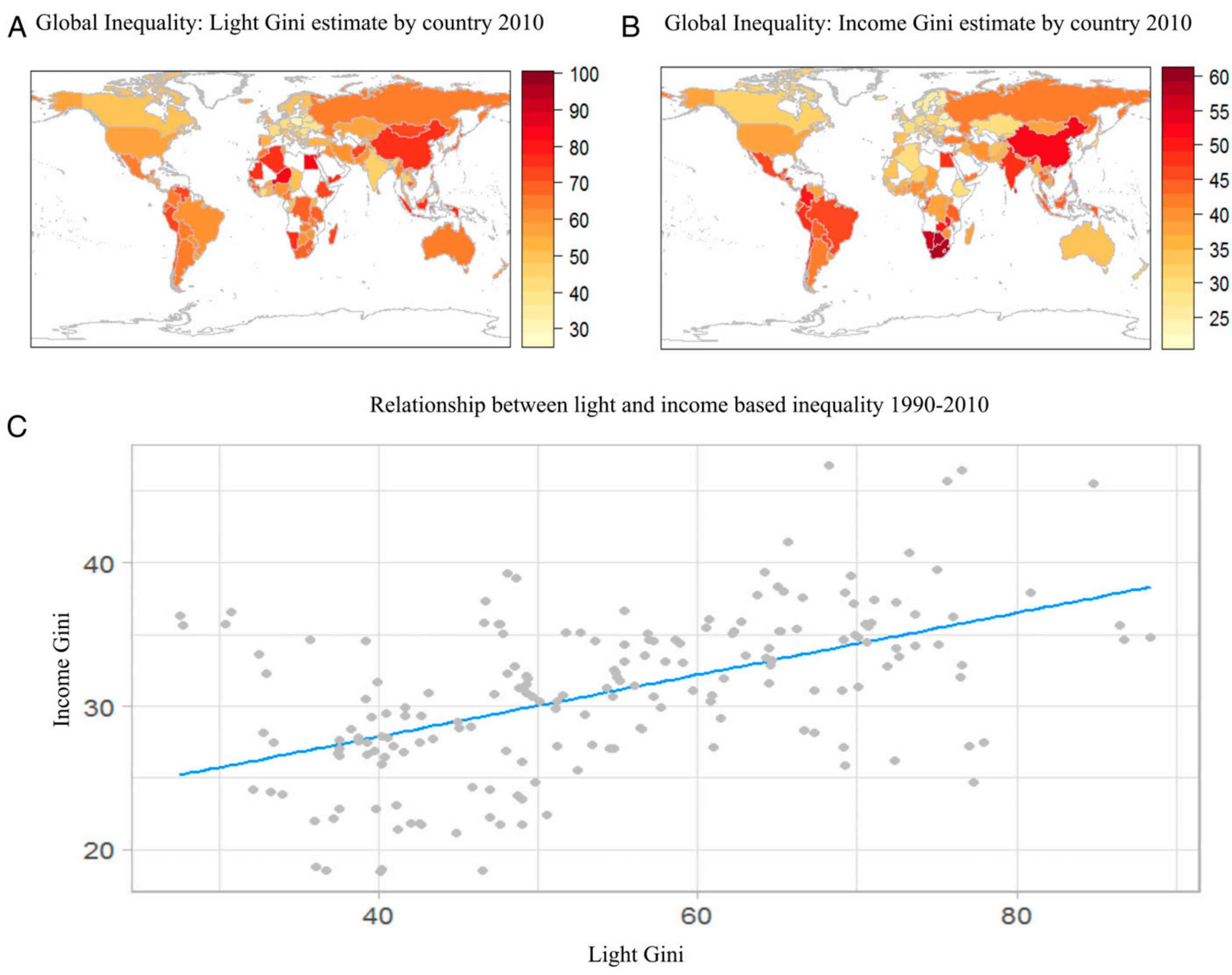

Fig. 1. (*A* and *B*) Comparison of light- and income-based inequality globally for 2010. (*C*) Model 4 (Table 1) fit of global national light and income Gini estimates for years 1990 to 2010. The Pearson's correlation coefficient is 0.44. In a linear mixed model controlling for production and population with year as the random effect, light-based Gini estimate explains 73% of the variation in the available income-based Gini estimates (Table 1, model 3).

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Table 1. Statistical relationship between income inequality, light-based inequality (light Gini), and covariates (log POP and log GDP) at a national level

	Dependent variable: Income Gini			
Independent variables	(1)	(2)	(3)	(4)
Fixed effects, estimate (SE)				
Light Gini	0.33*** (0.04)	0.29*** (0.04)	0.20*** (0.03)	0.17*** (0.03)
log POP		1.56*** (0.36)	6.64*** (0.39)	6.83*** (0.41)
log GDP			−5.70*** (0.35)	−5.88*** (0.37)
Intercept	15.65*** (2.65)	−7.82 (5.95)	63.15*** (5.85)	66.88*** (6.10)
Year as random effects	Yes	Yes	Yes	No
Year (intercept)	2.85	2.86	2.22	—
Observations	191	191	191	191
No. of countries	57	57	57	57
No. of years	5	5	5	5
R^2	0.33	0.39	0.73	0.69
AIC	1,345.00	1,329.03	1,166.30	1,174.45
AICc	1,345.21	1,329.35	1,166.76	1,174.77

The data for the years 1990, 1995, 2000, 2010, and 2010 are used. Columns 1, 2, and 3 show results for linear mixed models fitted using restricted maximum likelihood estimation, while column 4 is only fitted with fixed effects. Best-fit model is shown in column 3 based on its highest R^2 and lowest AIC and AICc consistently. log GDP, log-transformed gross domestic product; log POP, log-transformed population count.
$^{***}P < 0.001$.

income data from the American Community Survey (27) and the Frank–Sommeiller–Price Series (28). Encouragingly, on this spatial level, we still find a significant Pearson's correlation coefficient of 0.50 between income and light Gini in pooled observations (Fig. 3*B*). Both indicators corroborate, among other things, that the western and southern areas of the United States are more unequal than northern and central states (Fig. 3 *A*, *C*, *D*). A detailed analysis including results for the separate years is provided in *SI Appendix*, *Methods*. As an additional check of the robustness of the relationship between NTL patterns and inequality, we also analyzed the relationship between the top 5 and 1% incomes shares and the analogous NTL-based metric for the

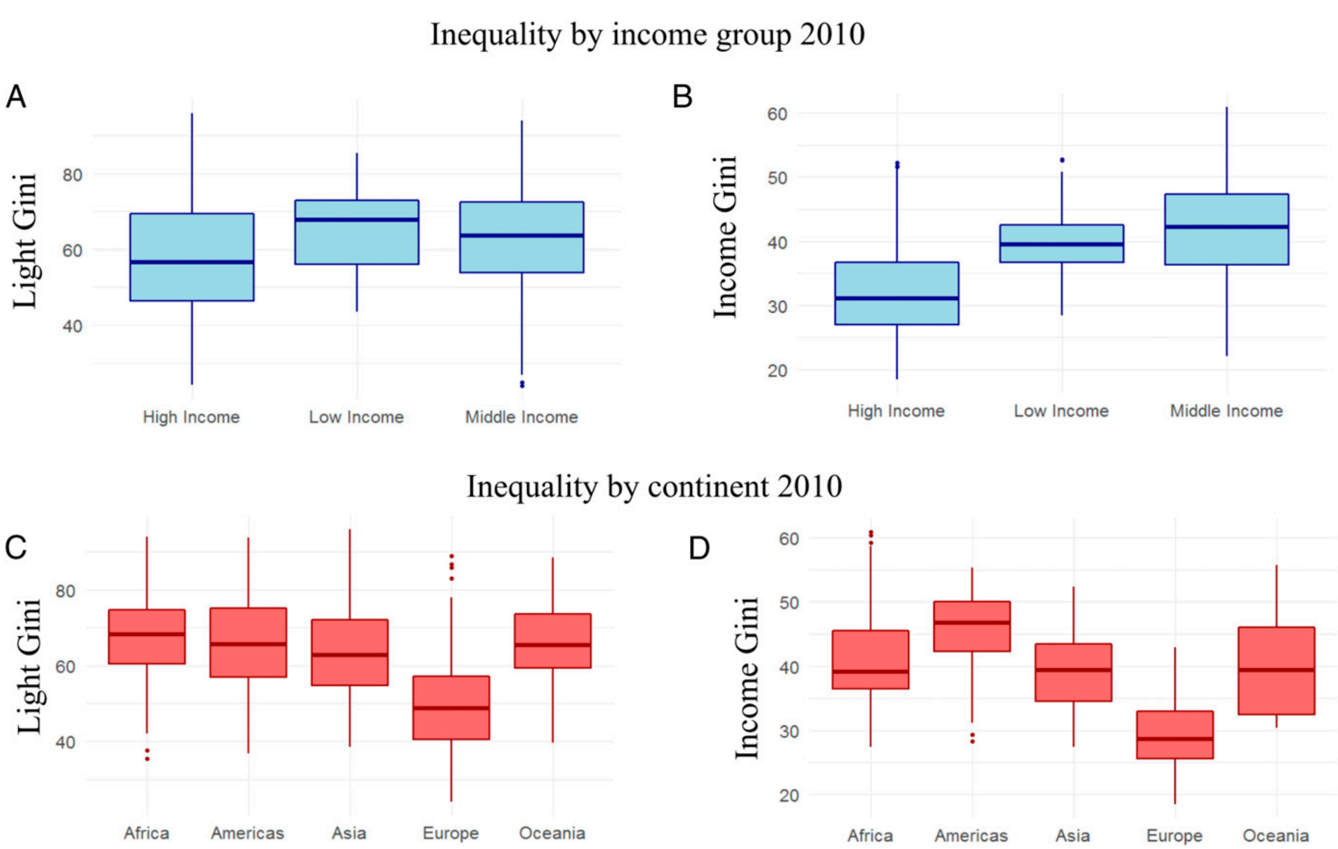

Fig. 2. Light- vs. income-based estimates of inequality by region and income groups. Inequality by income group 2010: (*A*) light Gini and (*B*) income Gini. Inequality by continent 2010: (*C*) light Gini and (*D*) income Gini.

50 US states (*SI Appendix*, Table S3 has details). Correlations were all significant for both the 1 and the 5% top income shares, except for the year 2010 where correlations were still positive but not significant.

Inequality at Finer Scales. We cannot test our proxy at finer scales as so far, georeferenced income census data are not available. Nonetheless, the possibility that light-based inequality estimates may make sense at fine resolutions is supported by small-scale empirical work using data at the household level to show that the estimation of income from NTLs is possible at fine scales (29). Therefore, we produced a global 1°-resolution map of our light-based inequality proxy (Fig. 4). Results suggest hot spots of inequality in areas within eastern China, southern Africa, central Brazil, northwest Egypt, Portugal, and close to coastal areas of the United States.

Monitoring Inequality over Time. The correlation between light- and income-based measures of inequality across countries and states does not translate to time series correlations. We found no significant relationship between the trend of light and trends in reported income distributions over time (*SI Appendix*, Fig. S3). This is consistent with earlier work showing that in time series, the correlations between national NTLs and GDP were not significant (20, 23). The lack of correlation does not necessarily mean that light-based inequality trends cannot carry a meaningful signal, as trends in traditional income estimates may be spurious as well. Nonetheless, we decided not to pursue the trend analyses further at this phase.

Effect of Sensing Resolution. Our model analysis shows that segregation as well as the resolution of sensing may be expected to influence light-based inequality estimates (*SI Appendix*, Fig. S1). To explore whether a higher spatial resolution would affect the outcome, we, therefore, repeated our analyses on the SNPP-VIIRS (Suomi National Polar-Orbiting Partnership Visible and Infrared Imager/Radiometer Suite) data (*SI Appendix*, *Methods* has descriptions of the data). For this newer source, fewer countries with matching income Gini estimates were available. Nonetheless, the reanalysis yielded similar results (*SI Appendix*, Fig. S2 and Table S4), suggesting that resolution is not a major limiting factor for estimating inequality from patterns of light emissions.

Discussion

The consistent relationship we find between our light-based proxy and traditional estimates of income inequality is remarkable. The sources of information on which both measures of inequality are based are entirely independent. Neither of them are likely to accurately represent true economic inequality. Spatial variance in the average light emission per person is admittedly a rather indirect proxy. On the other hand, existing estimates of income inequality are notoriously error prone too (15, 30, 31). Therefore, it is not possible to accurately infer how well our light-based proxy might indicate "true" income inequality. Nonetheless, the fact that we find such consistent associations between our light-based proxy and other Gini estimates is encouraging.

There are several reasons why we should not expect a one-to-one relationship between light-based Gini and traditional estimates. For one thing, light is unlikely to be a precise indicator of income, but there may be other biases. For instance, segregation will vary between regions. As illustrated by our model analysis, a remotely sensed inequality proxy can only work if there is sufficient spatial segregation of income groups. The very fact that we do find a significant correlation to traditional income inequality estimates is thus consistent with the idea that spatial residential segregation is a near

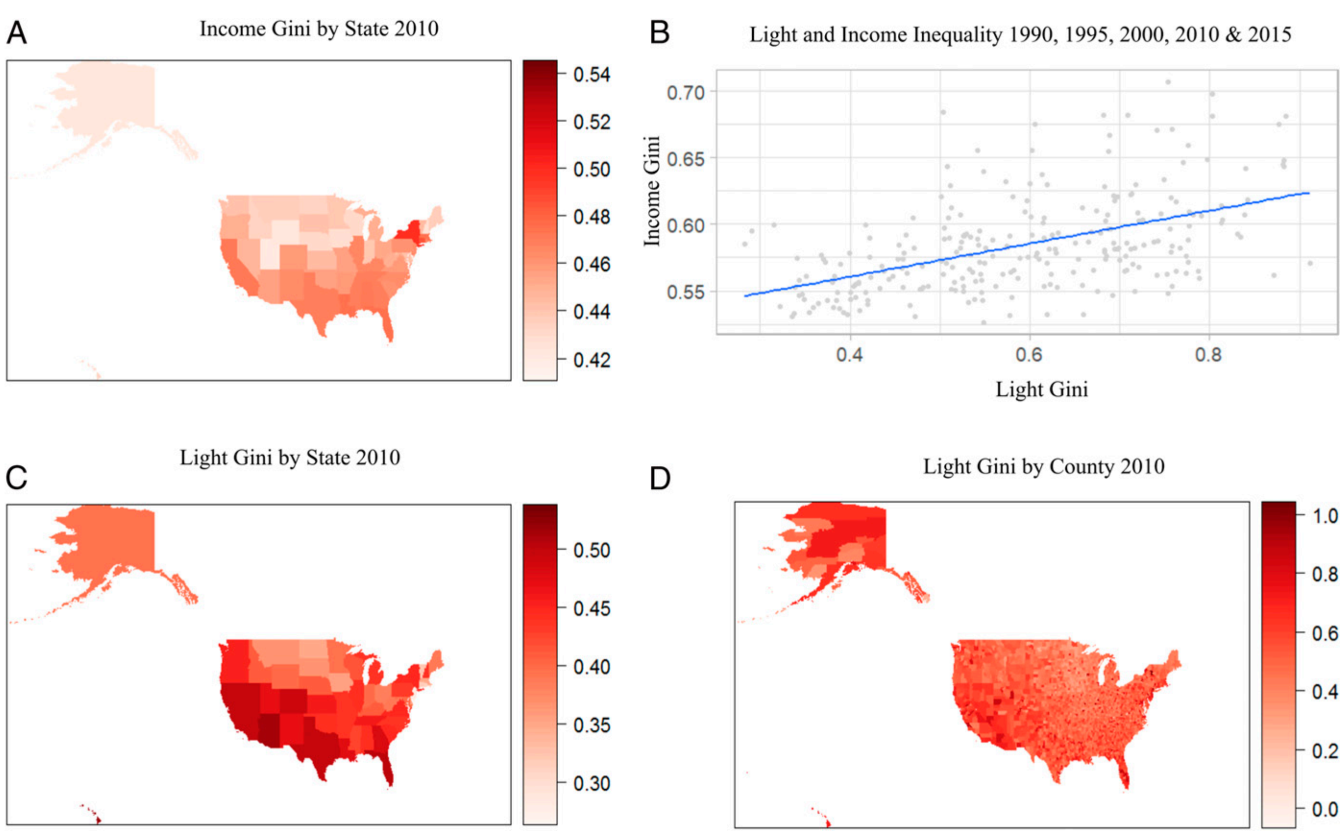

Fig. 3. (*A*) US state-level income Gini 2010. (*B*) State-level comparison between light- and income-based estimates of inequality for the United States (Pearson's correlation coefficient of 0.50). Light Gini 2010 for US state (*C*) and county levels (*D*), respectively.

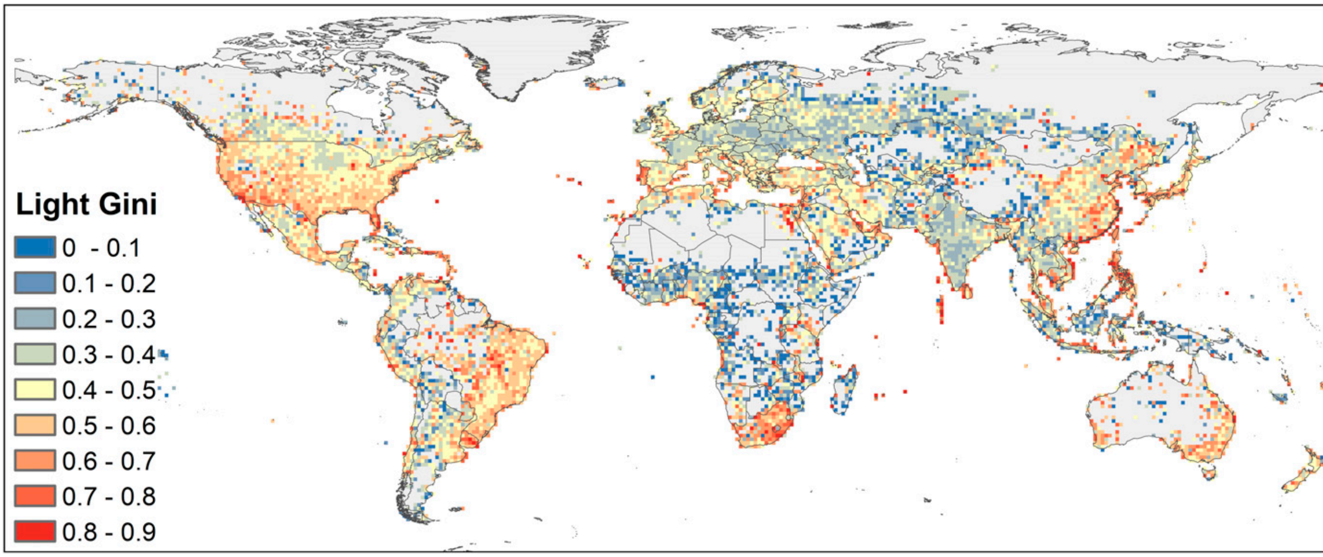

Fig. 4. Global distribution of light-based estimates of inequality for 2010 as measured by the Gini coefficient at a spatial resolution of 1°. Lower values of Gini represent more equal areas.

omnipresent phenomenon (24, 25). However, spatial residential segregation tends to increase with income inequality (32–34). This could cause remotely sensed inequality to come out more clearly in more unequal and hence, more segregated societies, thus increasing the contrast. Biases also exist in traditional inequality estimates. For instance, a considerable part of income may go unreported, the effect of which on traditional inequality estimates is uncertain. If the shadow economy mostly benefits low-income households, inequality may in reality be lower than official records suggest (15, 30, 31). On the other hand, if richer people tend to underreport their income, this makes top incomes elusive in survey-based estimates (5, 35), causing existing Gini coefficients to underestimate true inequality (potentially explaining the fact that income-based Gini estimates tend to be lower than our light-based estimates). Lastly, it is possible that inaccuracy of income reporting is correlated to inequality causing a systematic bias.

The bottom line is that we have presently no ways to quantify true economic inequality accurately. This implies that there is no gold standard to measure our remotely sensed proxy against. It is hardly surprising that there is quite some unexplained variance in the relationship between remotely sensed and traditionally measured inequality. However, what does that tell us? Given those uncertainties, what might our indicator contribute? As we see it, there are three ways in which light-based Gini estimates may complement existing measures of inequality: 1) provide a first estimate of inequality in regions where currently no estimates exist, 2) suggest inequality patterns at finer scales than we can currently measure, and 3) help sharpen existing inequality estimates. The third possibility may seem irrelevant if we consider existing estimates to be the gold standard. However, even if we know little about the uncertainty in our light-based estimates, we do know that existing measures have uncertainties as well. Taking a Bayesian perspective, it is better to have two uncertain estimates than one. There are various ways to build on this. For example, one could mark situations in which the two measures strongly deviate as cases for further scrutiny.

In conclusion, there are fundamental limitations to estimating economic inequality from remotely sensed NTL. However, the same is true for other approaches to estimating inequality. While it is widely acknowledged that inequality has profound effects on the functioning of societies, data remain frustratingly scarce. The remotely sensed proxy we propose may help in starting to fill some of the voids by providing estimates where none exist. It would be especially useful if our approach could be validated for higher spatial resolution, as this might pave the way for exploration of links to variables that are thought to be associated to inequality such as social mobility, trade, biodiversity, resilience to natural disasters, and resource use.

Materials and Methods

We estimate a proxy for economic inequality using a combination of NTL and population data. For light, we use the annual average visible, stable lights and cloud-free coverages data from the The United States Air Force Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) version 4 at a spatial resolution of 0.00833 decimal degree (~1 km), publicly available at https://ngdc.noaa.gov/eog/ (36). DMSP-OLS had multiple satellites sensing NTL from 1992 to 2010. For years when two satellites operated, like in 2000 and 2005, we used the satellite F15 data. Data for 2015 are also available via a newer but different dataset VIIRS SNPP. To avoid comparing across datasets, we refer the interested reader to *SI Appendix*, *Methods* for explanation and analysis with the VIIRS 2015 data for the national level. For the subnational level, since not enough data and examples are available, we include 2015 US state-level data in both Fig. 3 and *SI Appendix*, Fig. S3. For the population, we use the UN (United Nations)-Adjusted Population Count Gridded Population of the World GPWv4 and GPWv3 datasets by SEDAC (Socioeconomic Data and Applications Center) at 0.00833 decimal degree, publicly available at https://sedac.ciesin.columbia.edu/ (37). Combining NTL and population datasets from 1990 to 2010, we analyzed five yearly time points from 1990 to 2010 globally. Since in 1990, NTL data were unavailable, we use the earliest available dataset (i.e., from 1992) as an approximation. For country-level net income Gini estimates, we use The Standardized World Income Inequality Database (SWIID) version 6.1 (38) available at https://fsolt.org/swiid/. More details about country-level data can be found in *SI Appendix*, *Methods*.

The close relationship between NTL and a range of economic indicators, as alluded to in the text, makes light intensity a suitable measure to assign economic prosperity or income spatially. However, areas like cities are brighter not only because they are more economically active but also, because they are more densely populated. To take spatial population into account, we calculated average LPP (i.e., available NTL data divided by population density estimates) globally at five yearly time points between 1990 and 2010. At these 5-y time points, we overlaid the light and population raster data (both at a resolution of 0.00833 decimal degree) and then derived LPP by dividing NTL by the population count per grid cell. For calculating LPP, we only included those grid cells which had an NTL value greater than zero and a population count of greater than one. In this way, places with too few houses and/or places without detectable anthropogenic lights were discarded (e.g., industries, deserts, water bodies, forests, and the like). Assuming NTL captures the economic prosperity spatially (20, 23), inequality is then inferred from the distribution of LPP, over a specified spatial scale. Since inequality is an

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aggregate quantity, calculations for Gini coefficients based on LPP were done mainly at two levels—first, a coarser national level and second, a finer subnational 1°-grid level.

National- and state-level light-based inequality maps were generated to validate light-derived Gini coefficients with corresponding available estimates of income-based Gini estimates for the globe and the United States, respectively, using a mixed model approach. To achieve this, light-based Gini coefficients were calculated using LPP values within the administrative boundary of each country and each state of the United States, respectively. For most developing countries, income inequality estimates are prone to data comparability and quality issues, as already explained in the text, and hence, we set a cutoff of less than or equal to one as per Solt's (38) SWIID SEs to exclude estimates with large CIs. For US states, although the data are of good quality, our light-based estimate is prone to insufficient sensitivity of the satellite sensor for detecting very low or very high light intensities (the saturation problem) in some areas (39). Moreover, estimates based on areas with low lights can lead to excessive noise and outliers in the dataset.

Grouping observations by available years for the same set of countries, we use a mixed model approach to study the relationship between light and income Gini, taking into account the randomness of available years. Available years would have been different if, for example, the satellite was launched at a different time or kept for a longer duration. In the mixed model, years and light Gini are included as random effects intercept and slope, respectively. Furthermore, a parsimonious set of covariates is included to control for country-specific features such as economic output and population:

$$IG_{ij} = \beta_0 + \beta_1 LG_{ij} + \beta_2 \ln(GDP)_{ij} + \beta_3 \ln(POP)_{ij} + b_{0j} + b_{1j} LG_{ij} + \varepsilon_{ij}$$
$$\varepsilon_{ij} \sim N(0, \sigma^2),\ b_j \sim N(0, B).$$

Subscript ij refers to the respective estimate of country i in year j. Here, IG_{ij} refers to income Gini, LG_{ij} is light Gini, GDP_{ij} is the country's GDP (constant 2010 US dollars), POP_{ij} is the country's population count, b_{0j} is year random intercept, $b_{1j}LG_{ij}$ is the year random slope, ε_{ij} are the error terms, σ^2 is the variance of the error terms, and B is the variance–covariance matrix of the random effects. Here, the fixed part captures the overall relationship between light and income Gini, while the random part informs how that relationship varies across years. Table 1 reports model comparison and results. The reported generalized linear mixed model version of the R^2 is interpreted as the variance explained by the entire model, including both fixed and random effects, and is calculated using the Nakagawa and Schielzeth (40) method. AIC (Akaike information criterion) and AICc (AIC corrected for small sample size) are used to select model 3 as the best fit. Here, AICc is approximately equivalent to carrying out a leave one out cross-validation (41).

For fine-grain quantification of light-based inequality globally, we calculated Gini coefficients of LPP within 1°-grid cells. A static window approach was used to calculate focal values of light Gini for every 1° window. This resulted in fine-resolution (1°) global maps of light-based inequality for years 1990, 1995, 2000, 2005, and 2010. Data on light-based estimates of light-based inequality, and the code used for the analysis and generating figures are available at the public server Zenodo (https://doi.org/10.5281/zenodo.4635734) and can be downloaded with open access. The analysis was carried out in R (https://www.r-project.org) using the packages raster, rasterVis, sp, rgdal, ggplot2, and mixtools and Python (https://www.python.org/) using numpy, matplotlib, scipy, and statsmodels.

Data Availability. Data on light-based estimates of light-based inequality, and the code used for the analysis and generating figures are available at the public server Zenodo (https://doi.org/10.5281/zenodo.4635734). All study data are included in the article and/or *SI Appendix*.

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