Measuring Inequality using Geospatial Data

(link to paper)

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Abstract

The main challenge in studying economic **inequality** is limited **data availability**, which is particularly problematic in developing countries. We construct a measure of **economic inequality for 234 countries/territories from 1992 to 2013** using **satellite data** on **nightlights and gridded population data**. We obtain a measure that is significantly correlated with cross-country variation in income inequality. We provide three applications of the data in the fields of health economics and international finance. The results suggest that the **light-based inequality** measure can **capture more enduring features of economic activity** that are not directly captured by income.

Motivation

Traditional measures of inequality tend to rely on **national accounts and household survey data**. Both sources are prone to design differences and scattered availability, which is especially true for survey data[1].

Issues include **under-sampling** of richer households[2], **tax evasion** and other consistency issues[3]. Finally, the **informal sector** and shadow economy transactions pose additional threats to the reliability of these data[4].

We construct an alternative measure by using **worldwide satellite data on nighttime light emission** and match them with data on geo-located population counts to construct Gini-coefficients. The greatest advantage of this approach is the **consistent coverage** provided by the geospatial source data across countries.

Data and Approach

Night Lights Data:

- Defense Meteorological Satellite Program (DMSP) data generated by the Earth Observation Group (EOG) at NOAA's National Center for Environmental Information (NCEI). Available at annual frequency between 1992 and 2013.
- Full coverage of Earth's surface along the longitudinal dimension between 75 degrees north and 65 degrees south in latitude.
- We use the **average visible lights** version of the DMSP data.

Population Data:

- Gridded Population of the World (**GPW**) by CIESIN: Population census data matched to spatially-explicit administrative boundary data. Available on census-region-level (see upper left map below).
- LandScan (**LSC**) database by Oak Ridge National Laboratory: Disaggregated census counts within administrative boundaries with the support of ancillary data, such as land cover, roads, slope, urban areas, village locations, and high resolution imagery. Available on the pixel-level (see upper right map).

Economic Inequality:

- Calculation of census- and pixel-level **Gini-coefficients** using different parameters to map satellite data to actual economic numbers.
- **Weighting of Gini-coefficients** to maximize correlation with conventional income-based Gini-coefficients (**SWIID**[5]) → **Light-based Economic Inequality**

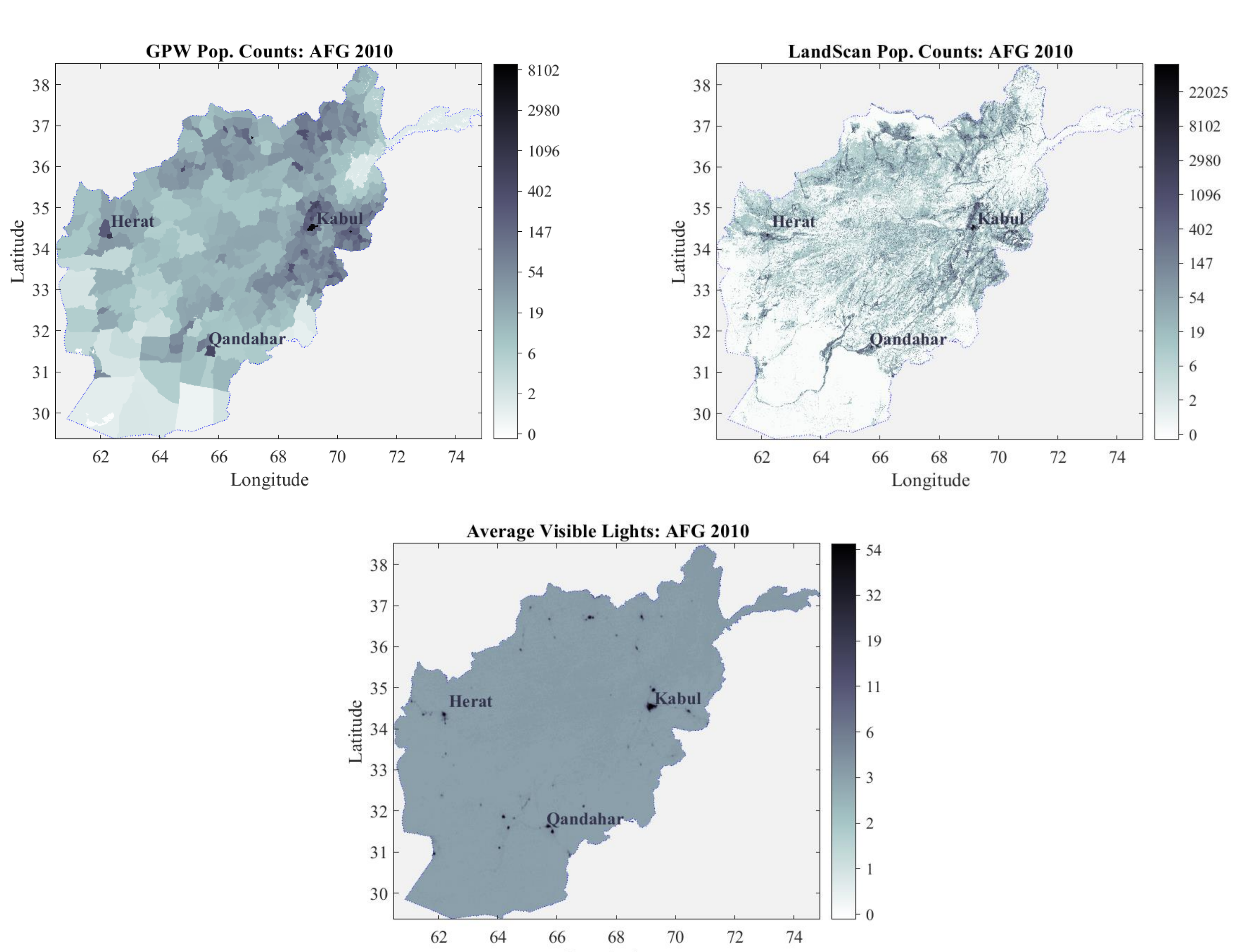

Figure 1. Afghanistan Geospatial Data in 2010.
1st row: GPW (left) and LandScan (right) population data;
2nd row: night lights data.

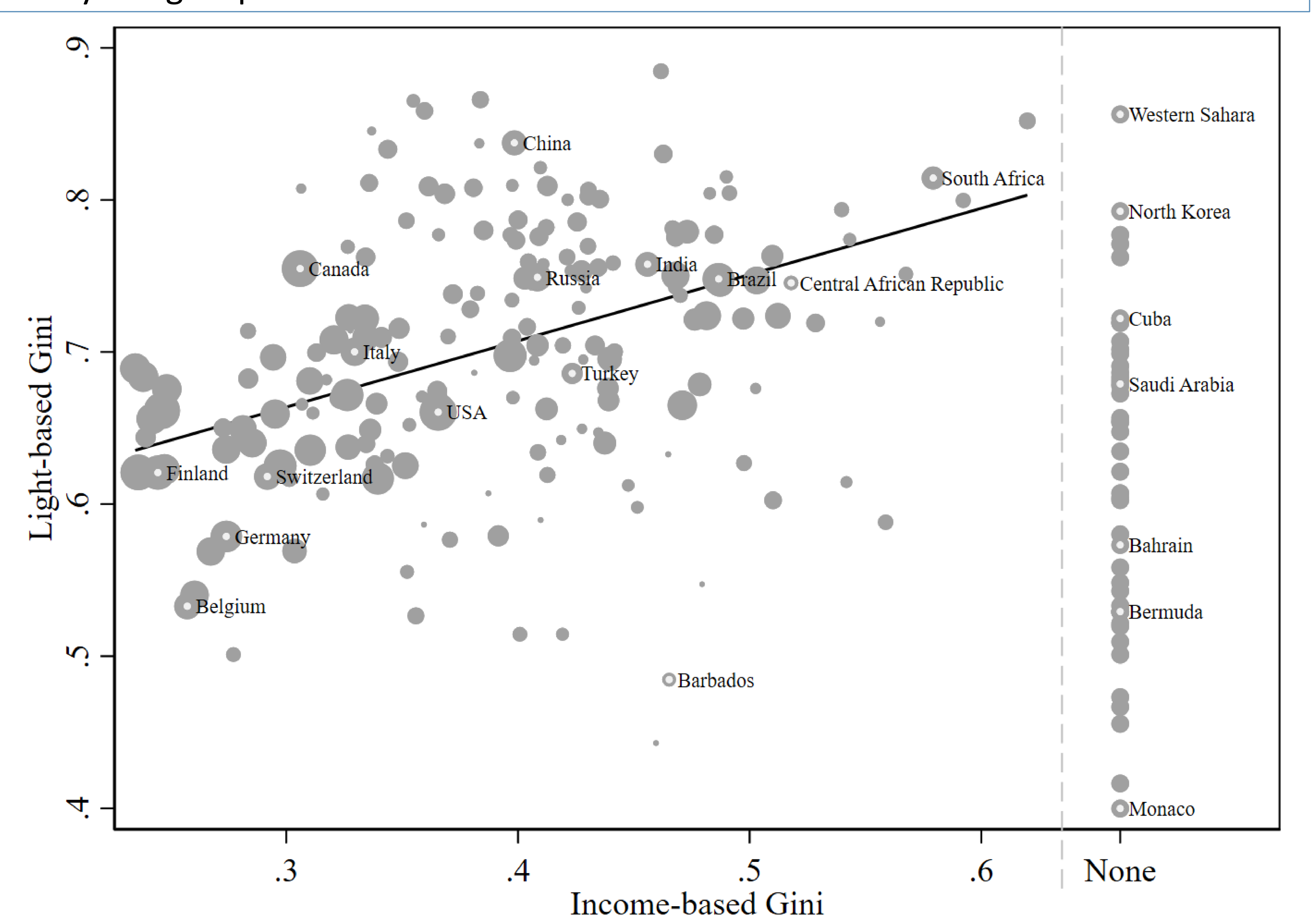

Figure 2. Light and Income-based Gini-Coefficients.

Applications

Applications show how light- and income-based inequality measures correlate with different determinants of inequality:

- Out-of-pocket health care expenditure
- Epidemics
- Financial liberalization

Empirical Approach:

$$G_{c,t} = \gamma z_{c,t} + \delta_t + \alpha_c + \epsilon_{c,t},$$

where $G_{c,t}$ is the income- or light-based Gini-coefficient. $z_{c,t}$ is the variable of interest from the applications. δ_t and α_c are time- and country-fixed effects.

Results: similar for light- and income-based inequality in the cross-section, however the results diverge in within-country estimations.

Interpretation: lights data are less prone to transitory income shocks while capturing additional aspects of the economy, such as informal economic activities, the distribution of productive means and household expenditures.

Conclusions

- **Main Contribution**: new measure of **economic inequality** based on geospatial data on nighttime light emissions and gridded population counts.
- Balanced sample of 234 countries and territories from 1992 to 2013.
- The measure is significantly correlated with conventional measures of income inequality across countries, but captures additional aspects, such as consumption, informal activities, infrastructure and wealth.

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Data Access:

https://www.ciesin.columbia.edu/data/global-geospatial-inequality/

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