Can Poverty Rates Be Estimated Using Satellite Data?

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Abstract— **Standard methods for estimating poverty rates produce aggregated results for individual countries or administrative units. There are a wide number of potential applications for disaggregated grids of population numbers in poverty. We have investigated the possible use the brightness of satellite observed nighttime lights along with along with gridded population count data in the estimation of poverty numbers. Preliminary results indicate that in general lighting is dimmer or absent in areas with high poverty numbers. It is likely that several calibration curves would need to be developed to account for cultural and technological differences in lighting.**

I. Introduction

Poverty remains one of the chronic dilemmas facing civilization during the 21st century. It is estimated that 42% or 2.6 billion people live in poverty [1]. Poverty is the general term describing living conditions that are detrimental to health, comfort, and economic development. There are different forms of poverty, such as inadequate supply or quality of food, water, sanitation, housing, clothing, schools, access to electricity and medical services. In locations where poverty levels are high there is typically a convergence of inadequacies across several of these areas. Widely noted consequences of poverty include higher infant mortality, shorter life spans and lower literacy rates. Poverty is also closely associated with environmental degradation [2].

Standard methods for estimating poverty rates are based on government records (e.g. taxes and medical) or on the analysis of household surveys. Differing standards in defining poverty make pooling of poverty data problematic. In addition, not all countries conduct the surveys and repeat cycles for the survey vary substantially.

Poverty maps have emerged as important tools for targeting aid and development resources [3,4]. Poverty maps traditionally depict a single measure or index value for an entire administrative unit, such as country or state. Spatially disaggregated global maps of the numbers of individuals living in poverty, based on a consistent definition of the poverty line would be extremely useful for targeting of efforts to reduce poverty [5]. Part of the value of spatially disaggregated data is that their aggregation can be tailored to the application. If spatially disaggregated poverty maps could be updated on an annual or semi-annual basis, they could be used to track the effectiveness of poverty reduction efforts in specific localities and the consequences of natural disasters, epidemics, or conflicts.

Satellite sensors provide one of the few globally consistent and repeatable sources of observations. However, most satellite sensors are designed to observe natural systems - not differences in the living conditions of human populations. In this paper we explore the possibility that satellite observed nighttime lights could be combined with gridded population data to estimate poverty levels. The basic concept is that the brightness of lighting is used as an indicator of the wealth. Several previous studies have found a strong correlation between the brightness of DMSP lighting and economic measures such as Gross Domestic Product [6,7].

II. Data Sources

A. LandScan 2004

The U.S. Department of Energy, Oak Ridge National Laboratory has produced an evolving series of spatially disaggregated global population count data sets, known as LandScan [8,9]. The LandScan products are 30 arc second

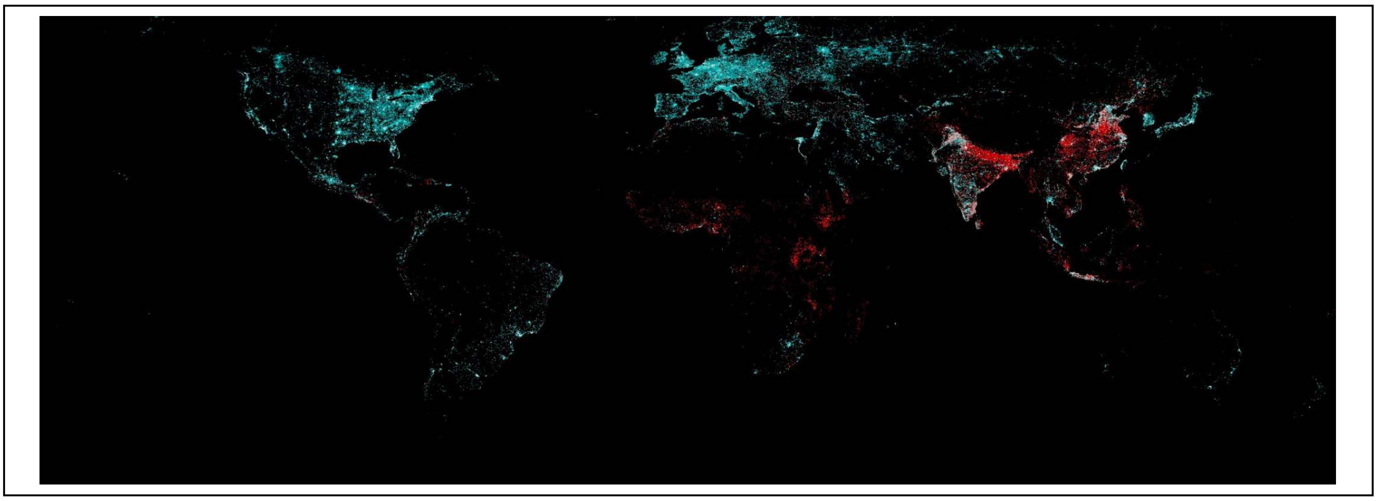

Figure 1. Color composite overlay of LandScan 2004 population count (red) and radiance calibrated nighttime lights (blue and green). Note the red and pink colors present where population count is high and lights are dim or not detected.

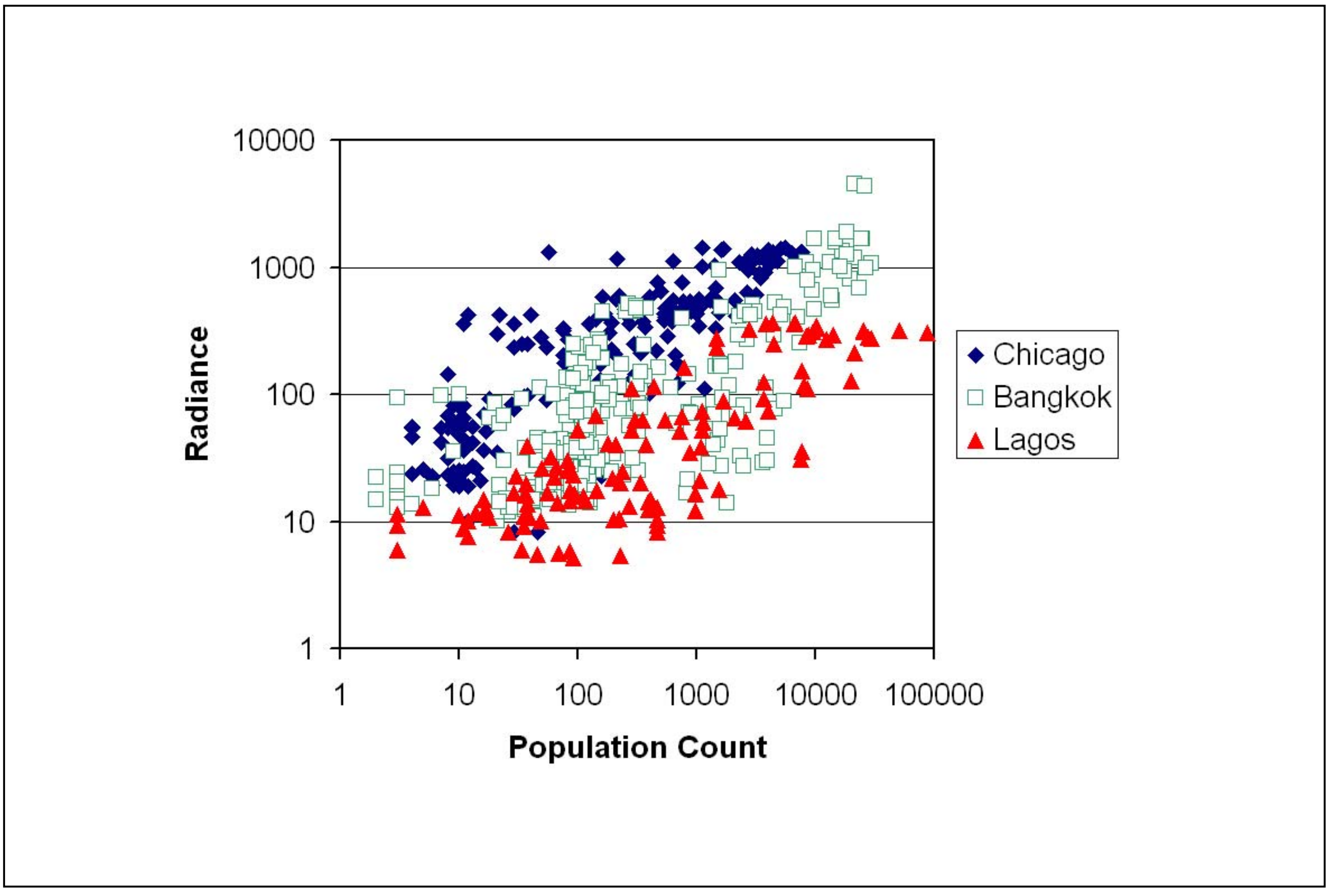

Figure 2. Satellite observed radiances from nighttime lights versus population count for three cities.

grids, corresponding to approximately one kilometer resolution at the equator. We used the 2004 version of LandScan, which included input from three satellite data sources: NASA MODIS land cover, topographic data from the Shuttle Radar Topography Mission (SRTM Rodriguez et al., 2005), and outline of human settlements from high resolution imagery. LandScan allocates reported population numbers across the landscape based on land cover, topography and the outline of human settlements. Note that LandSacn 2004 does not use nighttime lights as an input.

B. DMSP Nighttime Lights

The U.S. Air Force Defense Meteorological Satellite Program (DMSP) Opeartional Linescan System (OLS) has a unique capability for global mapping of lighting present at the earth's surface including cities, towns, villages, gas flares, heavily lit fishing boats and fires. A radiance calibrated nighttime lights product [10] was processed on the same 30 arc second grid used by LandScan. The product was generated using cloud-free section of nighttime visible band imagery from DMSP satellite F16 acquired during 2005 and 2006. The OLS gain was alternated between three overlapping gain settings (high, medium and low) to span the full range of lighting that can be detected by the sensor. The preflight sensor calibration was used to convert the digital num ber values into radiance units.

III. Results

A. Overlay of the grids

Overlay of the LandScan data and nighttime lights revealed that there are several parts of the world with high populations and little or no detected lighting. Figure 1 shows the overlay, with population count in red and nighttime lights in green and blue. The cores of many urban centers are white, indicating high population count and very bright lights. The blue-green color found in much of North America and Europe indicates that lighting was detected even in areas having low to moderate population count values. The red areas indicate locations where population count is high and lighting is either not detected or quite dim. These red areas appear to be the regions of the world where poverty levels are highest. This includes portions Africa, India, China, and Southeast Asia.

B. Urban transects

To examine the differences in urban lighting between wealthy and poor countries a series of transects were drawn the overlay image shown in Figure 1. The transect data were extracted and have the radiance values of the lights have been plotted against population count. Figure 2 shows the results from three cities: Chicago (USA), Bangkok (Thailand) and Lagos (Nigeria). These three cities span the range from wealthy to poor. Lagos has very dim lighting relative to population count - an indicator of high poverty levels. Chicago has relatively high lighting levels relative to population count, indicating low levels of poverty. Bangkok is in between, indicating moderate poverty levels.

IV. Conclusion

For many years the remote sensing community has used band ratios and indices to estimate variables such the sediment loads in water or green biomass on land. One of the classic examples is the "vegetation index" which is calculated by dividing the NIR radiance by the red radiance. The vegetation index works by contrasting the bright reflectance of sunlight by green leaves in the near-infrared against the strong absorption of red light by chlorophyll molecules. The evidence presented here suggests that a similar "poverty index" could be calculated by dividing population count by the brightness of nighttime lights.

There are several shortcomings for nighttime lights in poverty estimation that should be acknowledged. The detection of lighting is a sure indicator of the presence of an electric power grid. However, poverty is a multifaceted phenomenon for which access to electricity is only one aspect. In areas where no lighting is detected there is no basis to discriminate variations in poverty levels without bring in additional data. For instance, there are many rural areas in wealthy countries where lighting is too dim to be detected by the OLS. In these cases poverty rates may be overestimated. Another issue is that there are cultural preferences for lighting and technological differences in lighting between different countries that would need to be addressed to improve the accuracy of poverty estimates derived based on nighttime lights.

These preliminary results indicate that there is substantial potential for using satellite observed nighttime lights in combination with gridded population data in estimating poverty levels.

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