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A global poverty map derived from satellite data

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ABSTRACT

A global poverty map has been produced at 30 arcsec resolution using a poverty index calculated by dividing population count (LandScan 2004) by the brightness of satellite observed lighting (DMSP nighttime lights). Inputs to the LandScan product include satellite-derived land cover and topography, plus human settlement outlines derived from high-resolution imagery. The poverty estimates have been calibrated using national level poverty data from the World Development Indicators (WDI) 2006 edition. The total estimate of the numbers of individuals living in poverty is 2.2 billion, slightly under the WDI estimate of 2.6 billion. We have demonstrated a new class of poverty map that should improve over time through the inclusion of new reference data for calibration of poverty estimates and as improvements are made in the satellite observation of human activities related to economic activity and technology access.

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1. Introduction

Poverty has emerged as one of the chronic dilemmas facing civilization during the 21st century. Based on data from the World Development Indicators (World Bank, 2006) approximately 42% or 2.6 billion people live in poverty. 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, 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 often associated with environmental degradation and loss of biodiversity as the poor often end up using local natural resources unsustainably (Snel, 2004). The United Nations Millenium Development Goals includes a 50% reduction in extreme poverty by the end of 2015. Economic analyses (Sachs, 2005) indicate that eliminating poverty is a realistic objective.

The primary source for statistics on global poverty is the World Bank, which has collected and distributed national level data on poverty levels since 1990. Their methods are based on the analysis of household surveys conducted in almost 100 developing countries. Survey questions cover sources of income, consumption, expenditures, and numbers of individuals making up the household. Most surveys are conducted by government employees. Two styles of poverty data are produced—national poverty line data and international poverty line data. Individual countries establish their own poverty line for the national data. Differing standards in defining poverty make pooling the national poverty line data problematic. More recently, purchasing power parity has been introduced into the formulation of international poverty line data, which is specified in terms of the number of individuals living on less than $1.08 a day and $2.15 a day at 1993 international prices (World Bank, 2006) (Fig. 1).

There are a number of problems recognized with the World Bank poverty line data. Not all countries conduct the surveys, the currently available data were derived from surveys spanning 1988 through 2004 and the survey repeat cycle is uncertain. The intercomparability of the estimates is uncertain due to difficulties in reconciling consumption and income data, plus discrepancies in the purchasing power parity estimates for individual countries (Karshenas, 2004/5). It is also possible for governments to influence the outcome of the surveys since they design the questions, select the areas for survey and conduct the interviews. The use of the $1.08 and $2.15 per day standards for the international poverty line data is not applicable to prosperous countries such as the USA, where 12% of the population is listed in poverty (De Navas-Walt et al., 2005).

Poverty maps have emerged as important tools for targeting aid and development resources (Sachs, 2000; Sachs et al., 2001;

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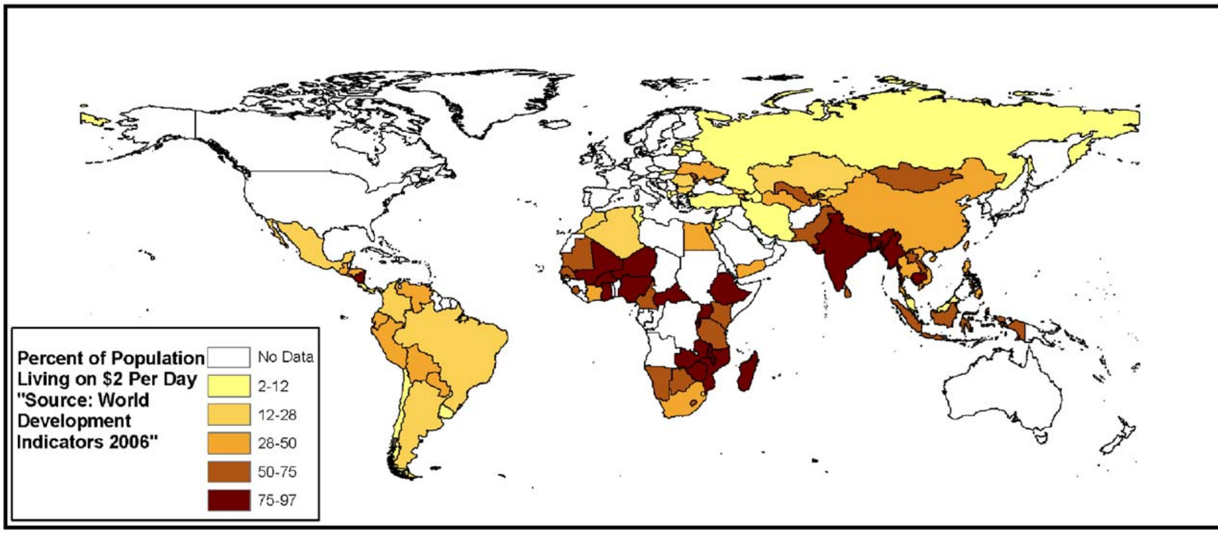

Fig. 1. Map of poverty levels for countries reporting international poverty line data (percent of population living on $2 per day or less) from World Development Indicators 2006. Note that a number of countries have no data reported and that $2 per day poverty line is not applicable to developed countries.

Henninger and Snel, 2002; CIESIN, 2006). 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 (Hentschel and Lanjouw, 1998). Part of the value of spatially disaggregated data is that they can be aggregated to multiple levels: national, state, sub-state or municipal. 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 images could make it possible to update spatially disaggregated poverty maps on an annual or semi-annual basis.

Satellite sensors provide one of the few globally consistent and repeatable sources of observations. In the environmental sciences, satellite data have proven crucial for global mapping and global assessment of processes such as deforestation. Fewer applications for satellite data have been developed in the social and economic sciences. In part, this can be attributed to the fact that most earth observation satellite sensors are optimized for observation of natural phenomena (such as the movement of clouds and the characteristics of the land and sea surface) that are not directly related to socio-economic measures such as population density, living conditions, and economic activity. Previous efforts related to the integration of spatial information derived from satellite imagery and survey data to predict poverty includes the Poverty Mapping Project of the Center for International Earth Science Information Network (CIESIN). In a similar study undertaken in Uganda (Rogers et al., 2006; Robinson et al., 2007) researchers combined household level expenditure data derived from surveys with satellite derived variables such as land surface temperature, normalized difference vegetation index (NDVI), air temperature, and a digital elevation model to describe, explain and predict the spatial distribution of poverty. Ebener et al. (2005) utilized nighttime light imagery and population to model the distribution of income per capita, as a proxy for wealth, at the country and sub-national level and found strong correlation to key health indicators. Each of these studies strove towards a spatially disaggregated mapping of poverty which could be used for improved planning of efforts to improve the living conditions of the affected populations.

In this paper, we present the first spatially disaggregated global map of poverty numbers derived from satellite data from four distinct sensor types. This map is prepared solely from Landscan population count and DMSP nighttime lights. The poverty map is based on the assumption that areas with higher population counts in developing countries would be poorly lit and therefore have higher percentages of poor people (lights being considered as a proxy for wealth) and vice versa. From the disaggregated data, we have produced both national and sub-national estimates of poverty levels for a very large part of the world.

2. Materials and methods

Two spatially disaggregated data sources have been combined to form a global poverty index: LandScan population counts and DMSP nighttime lights. The index is formed by dividing population count by the average visible band digital number from the lights. In areas where no lighting is detected the lights data set have a value of one—thus passing the LandScan population count into the poverty index. Both data sources are produced on a 30 arcsec grid and two grids are produced with no data sources in common. Since the nighttime lights product has a latitudinal extent of 65 south–65 north, this determined the extent of the analysis. This result in a truncation of administrative units that straddle the 65° north latitude line and the small number of administrative units located entirely above this line have not been included in the analysis. Below is a description of the two data sources.

2.1. LandScan 2004

The US Department of Energy, Oak Ridge National Laboratory has produced an evolving series of spatially disaggregated global population count data sets, known as LandScan. The basic concept of the LandScan data sets is to perform a spatial allocation of census reported population numbers based on models developed with spatially disaggregated data. The term population count is used instead of population density—that is based on residence.

On a population density grid commercial centers and airports have very low numbers, despite the fact that there are substantial numbers of people present during certain hours. Population count products, also referred to as ambient population, attempt to represent the spatial distribution of population based on person hours.

The first LandScan product (Dobson et al., 2000) used DMSP nighttime lights for the mapping of human settlements. However, the nighttime lights were subsequently dropped (Bhaduri et al., 2002) due to the overt effect of economic development on the extent and brightness of lighting. We used the LandScan 2004 products, which included input from three satellite data sources: NASA MODIS land cover (Friedl et al., 2002), the topographic data from the Shuttle Radar Topography Mission (SRTM) (Rodriguez et al., 2005), and the high-resolution land cover data of the Controlled Image Base (CIB) from the US National Geospatial Intelligence Agency (NGA).

2.2. Nighttime lights

The US Air Force Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) has a unique capability for global mapping of artificial lighting present at the earth's surface. DMSP operates satellites in sun-synchronous orbits with nighttime overpasses in the 8–10 pm range local time. With a swath width of 3000 km and 14 orbits per day, each OLS instrument is capable of generating a complete coverage of nighttime data in a 24 h period. The OLS is an oscillating scan radiometer with two spectral bands. The visible band pass straddles the visible and near-infrared portion of the spectrum (0.5–0.9 μm) and the thermal band pass covers the 10.5–12.5 μm region. DMSP–OLS is basically designed for global observation of cloud cover. At night, the visible band is intensified with a photomultiplier tube (PMT) to permit detection of clouds illuminated by moonlight. The light intensification enables observation of faint sources of visible–near-infrared emissions present at night on the earth's surface including cities, towns, villages, gas flares, heavily lit fishing boats, and fires. The low-light-sensing capabilities of the OLS at night permit the measurement of radiances down to 10^{-9} W/cm^2/sr. NGDC has had a program to produce global cloud-free composites of DMSP nighttime lights since 1994 (Elvidge et al., 1997).

A set of cloud-free nighttime lights composites was produced for the year 2003 using archived data from DMSP satellite F-15. The data were screened to exclude clouds based on the OLS thermal band data. While the OLS swath is 3000 km, only data from the center of the swath was composited. Lights detected in the center of the swath have better geo-location, have more consistent radiometry and are smaller when compared to lights at the edge of scan. The OLS data are further screened to exclude sunlit and moonlit data, plus data affected by "glare", which occurs under certain geometries where the spacecraft is in sunlight while viewing a dark earth. The annual composites were filtered to remove background noise and fires. The remaining features vary in brightness from 2–3 digital numbers (DN) to the saturation DN of 63 (six bit data). There are small areas of saturation in the centers of large cities.

The linkage between the extent and brightness of DMSP nighttime lights and wealth has been noted by several studies. Elvidge et al. (1997) used stable light data products in their analysis and established a strong correlation between lit areas, gross domestic product (GDP), and electric power consumption for 21 countries at the national aggregate levels. The results established that economic activity and electric power could be estimated using OLS data. Again, the strong relationship between economic activity and CO_2 emissions with the total lit area were used to create global maps of these parameters by Doll et al. (2000). Doll (2003) used the cumulative radiance value in the radiance-calibrated nighttime image to develop area–GDP relationship at the national scale for the United Kingdom. This relationship was, however, not found to be valid at the sub-national scale. Sutton et al. (2007) also made an attempt to estimate sub-national GDP from the nighttime light images for the United States, China, India, and Turkey. The log–log relationship between the areal extent of urban areas and population was used to obtain an approximation of 'urban population' of every state and then this measure of urban population was used as a proxy measure of GDP in that state. Building upon these studies an original poverty map of the world is prepared. Conversely, the inability of the OLS to detect cities and towns in the poorest areas of the world has been cited as one of the systems shortcomings for population modeling (Balk et al., 2005).

2.3. The poverty index (PI) and calibration

The poverty index is calculated by dividing the LandScan 2004 population count by the average visible band digital number from the lights. In areas where population is present but no lights were detected the full population count is passed to the index. The concept of the poverty index is to create a gray-scale image that is adjusted to lower values in abundantly lit areas where economic activity is high (Fig. 2). High poverty index values occur in areas with high LandScan population count and dim (or no) lighting as detected by the OLS. Areas having a preponderance of high poverty index values include India, China, and Africa. Countries having low levels of poverty (such as the USA, Western Europe, and Japan) have a preponderance of low poverty index values.

A calibration for estimating the number of people living in poverty was developed based on the World Development Indicators 2006 international poverty line estimates for the

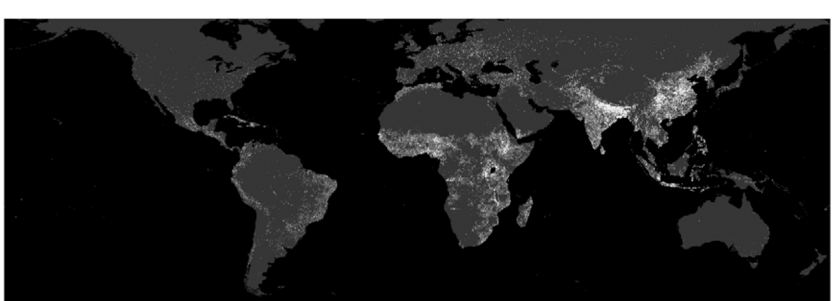

Fig. 2. Poverty index calculated by dividing LandScan 2004 population count by average digital number of DMSP satellite F15 nighttime lights from 2003.

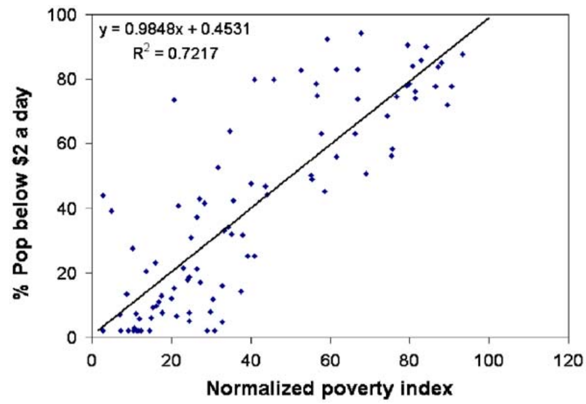

Fig. 3. Calibration of normalized poverty index (NPI) for estimation of poverty levels.

percentage of people living on $2 or less per day. To establish the calibration, the sums of the poverty index values were extracted for each country. This sum was then divided by the total population count and multiplied by 100.0 to form a normalized poverty index (NPI). The NPI was then regressed to the percentage of the population living on $2 per day or less (see Fig. 3).

3. Results

The calibration from Fig. 3 was applied to the NPI grid to get a percent estimate of poverty in each grid cell and then multiplied by the LandScan population grid to yield an estimate of the population count in poverty (poverty count). This is gray-scale image data that can be color coded or aggregated and is available at http://www.ngdc.noaa.gov/dmsp/download_poverty.html. The calibration was also applied to national level NPI and LandScan population counts to yield spatially aggregated poverty estimates. This was done for 233 countries to generate national poverty levels and poverty counts, which are presented in Table 1. Among the 81 countries having populations greater than 10 M those having poverty rate estimates greater than 80% are Ethiopia, Burkina Faso, Madagascar, Cambodia, Uganda, Tanzania, Malawi, and Niger (Table 2). Those having estimated poverty rates less than 10% include Taiwan, South Korea, Egypt, Saudi Arabia, Japan, Belgium, Netherlands, Italy, United Kingdom, USA, Canada, Czech Republic, Germany, Greece, Spain, Hungary, and France.

The procedure used to generate the national level poverty estimates was then applied at sub-national level for 2543 administrative units having LandScan population values above zero. These results are presented graphically in Fig. 4.

Many of the patterns present within individual countries match expected results, with lower poverty levels in the more prosperous areas. For instance, coastal China has lower poverty rates than interior area, northeastern India has higher poverty rates than western and southern India, and the prosperous Sao Paulo region has lower poverty rates than other parts of Brazil. The effects of lighting from gas flares, which reduce the poverty estimates, can be observed in coastal Nigeria. A comparison of the estimated poverty rates in the USA versus measured rates reported for 2004 by De Navas-Walt et al. (2005) revealed a RMSE of 4.22.

4. Discussion

A global map of poverty levels has been produced using a combination of four types of satellite data (DMSP lights, MODIS land cover, SRTM topography, and CIB). The MODIS, SRTM, and CIB data were used as inputs (along with census data) into a global population grid. DMSP lights were used as a measure of economic activity. The poverty index used to estimate poverty levels is calculated by dividing population count by the brightness of the nighttime lights. A calibration was developed using national level poverty levels reported by the World Development Indicators 2006. The resulting estimate for the number of people living in poverty is 2.2 billion, consistent with the 2.6 billion estimated by the World Bank (2006).

Since the resulting poverty data set is at 30 arcsec resolution—it can be aggregated to either national or sub-national levels. An accuracy assessment comparing the satellite-based poverty estimates to state level data for 2004 in the USA revealed an RMSE of 4.22. The extent to which the data values are accurate at the 30 arcsec level has not been assessed. It is likely that at the most disaggregate level (30 arcsec pixels) our poverty index is highly variable in its accuracy. For example a high poverty level in the favelas of Sao Paolo might have the same index value as a very low poverty level on Park Avenue in Manhattan. However, when aggregated to sub-national and national levels these kinds of errors average out and our indices correlate strongly with other independently derived measures of poverty.

The poverty estimate for Egypt of 3.3% points out one of the flaws with the use of DMSP lighting as an economic indicator. There are cultural variations in the use of lighting and these have not been accounted for in the current version of the poverty index. The WDI poverty estimate for Egypt is 43.9%. The low poverty estimate coming from the lights appears to be the result of population numbers being concentrated in the Nile river valley and delta, which is abundantly lit. In the USA the states of Vermont and Maine, known for their environmentally conscious development, have anomalously high poverty estimates, apparently due to their constrained use of outdoor lighting. Similar overestimations of poverty levels appear to be occurring in portions of Europe where sprawl development has been constrained by land policies designed to preserve rural lands. In several cases, such as coastal Nigeria, the inclusion of lights from gas flares has tilted the poverty estimates to lower levels. For areas such as these, better poverty estimates may be possible through use of local calibration data rather than the global set used in this study.

There are several additional known flaws with the DMSP nighttime lights product used in this study. The data used were from the operational OLS data collections in which the digital number values in urban centers are typically saturated at a digital number of 63 (six bit data). As a result, the poverty index values for many a wide range of urban areas were derived with a single denominator—63. At high population counts this results in erroneously high poverty index values. This problem could be resolved by the use of radiance-calibrated nighttime lights data which have no saturation. Unsaturated nighttime OLS data can be collected upon special request for use in the assembly of nighttime lights products with valid digital numbers in urban centers (Elvidge et al., 1999). However, there are problems in deriving accurate radiance values from OLS data due to the lack of on-board calibration for the OLS PMT. The coarse spatial resolution (2.7 km ground sample distance) of the OLS results in lighting features that are substantially larger than the physical sources of lighting present on the ground. While the data saturation and the size exaggeration results in errors in the poverty index values, these effects are widely distributed. Since the OLS data processing is consistent in all areas of the world, the OLS combined with the LandScan data provide the first globally consistent assessment of poverty.

Table 1
National and global poverty estimates based a poverty index formed by dividing population count by the brightness of satellite observed lighting.

Country	LS 2004	Poverty index	Normalized	Pop. at $2	Estimated % pop. in poverty	Pop. in poverty
	Pop. count	Pop./DN of lights	Poverty index			
Afghanistan	28,410,980	22,720,812	79.97194043		79.21	22,504,186
Albania	3,433,109	1,048,854	30.55114184	11.8	30.54	1,048,467
Algeria	31,545,580	6,488,516	20.56870091	15.1	20.71	6,532,824
American Samoa	52,085	6103	11.71738504		11.99	6246
Andorra	69,962	2508	3.584803179		3.98	2787
Angola	10,645,932	8,116,065	76.23630322		75.53	8,040,938
Anguilla	12,639	886	7.010048263		7.36	930
Antigua and Barbuda	65,157	4034	6.191199718		6.55	4268
Argentina	38,696,260	6,155,672	15.90766653	23.0	16.12	6,237,439
Armenia	2,997,641	745,416	24.86675356	31.1	24.94	747,668
Aruba	67,267	1401	2.082744882		2.50	1684
Australia	19,322,928	2,434,531	12.59918269		12.86	2,485,078
Austria	8,129,847	641,930	7.895966554		8.23	669,009
Azerbaijan	7,755,703	2,241,748	28.90451065	2.0	28.92	2,242,815
The Bahamas	272,594	28,337	10.39531318		10.69	29,141
Bahrain	600,058	10,023	1.670338534		2.10	12,590
Bangladesh	140,576,752	74,129,376	52.73231523	82.8	52.38	73,639,563
Barbados	268,632	9591	3.570311802		3.97	10,662
Belgium	10,365,412	365,976	3.530742435		3.93	407,379
Belize	207,691	85,576	41.20351869		41.03	85,216
Benin	7,293,065	4,880,697	66.92243933	73.7	66.36	4,839,555
Bermuda	25,489	763	2.993448154		3.40	867
Bhutan	2,089,054	1,743,478	83.45777562		82.64	1,726,443
Bolivia	8,722,603	3,112,077	35.67830612	42.2	35.59	3,104,296
Bosnia and Herzegovina	3,992,185	962,210	24.10233995		24.19	965,673
Botswana	1,646,061	907,605	55.13799306	50.1	54.75	901,268
Brazil	178,096,304	47,004,832	26.39292952	21.2	26.44	47,097,313
British Virgin Islands	18,734	1895	10.11529839		10.41	1951
Brunei	289,717	13,669	4.718052444		5.10	14,774
Bulgaria	7,496,528	1,123,072	14.98122864	6.1	15.21	1,139,968
Burkina Faso	13,545,902	12,137,364	89.60174081	71.8	88.69	12,014,253
Burundi	6,366,676	5,948,226	93.42749655	87.6	92.46	5,886,660
Byelarus	10,324,346	3,194,345	30.93992588	2.0	30.92	3,192,571
Cambodia	13,380,562	11,578,787	86.53438473	77.7	85.67	11,463,417
Cameroon	16,022,772	11,071,732	69.09997846	50.6	68.50	10,976,041
Canada	32,018,318	2,248,726	7.023248379		7.37	2,359,620
Cape Verde	3,62,955	1,35,551	37.34650301		37.23	135,135
Cayman Islands	26,487	1601	6.044474648		6.41	1697
Central African Republic	3,722,174	3,005,653	80.7499327	84.0	79.98	2,976,832
Chad	9,567,083	8,219,044	85.9096132		85.06	8,137,463
Chile	15,210,395	2,470,981	16.24534406	9.6	16.45	2,502,340
China	1,270,484,096	555,786,560	43.74604623	46.7	43.53	553,095,168
Cocos (Keeling) Islands	248	248	100		98.93	245
Colombia	41,348,352	9,982,628	24.14274697	17.8	24.23	10,018,241
Comoros	588,444	483,929	82.23875169		81.44	479,240
Congo	3,045,933	1,341,775	44.05136292		43.83	1,335,181
Congo, DRC	57,911,408	45,987,808	79.41061975		78.66	45,551,190
Cook Islands	14,069	4731	33.62712346		33.57	4723
Costa Rica	3,873,384	683,451	17.64480361	7.5	17.83	690,613
Cote d'Ivoire	16,304,796	9,032,927	55.40042942	48.8	55.01	8,969,504
Croatia	4,346,473	540,639	12.43856801	2.0	12.70	552,115
Cuba	11114198	3,717,823	33.45111361		33.40	3,711,671
Cyprus	748,246	46,350	6.19448684		6.55	49,036
Czech Republic	10,234,140	740,201	7.232664396	2.0	7.58	775,321
Denmark	5,262,941	608,894	11.56946278		11.85	623,485
Djibouti	188,692	100,749	53.39336061		53.03	100,073
Dominica	34,830	16,638	47.76916451		47.50	16,543
Dominican Republic	8,696,280	1,460,172	16.79076571	11.0	16.99	1,477,380
East Timor	1,004,007	877,431	87.39291658		86.52	868,643
Ecuador	12,734,118	3,378,047	26.52753021	37.2	26.58	3,384,399
Egypt	75,099,408	2,155,994	2.870853523	43.9	3.28	2,463,498
El Salvador	6,549,989	14,26,553	21.77947169	40.6	21.90	1,434,547
Equatorial Guinea	422,433	278,467	65.91980267		65.37	276,148
Eritrea	4,401,247	3,442,824	78.22383066		77.49	3,410,435
Estonia	1,306,149	321,127	24.58578615	7.5	24.67	322,164
Ethiopia	71,440,984	64,750,296	90.63466427	77.8	89.71	64,089,791
Falkland Islands (Islas Malvinas)	3211	1201	37.40267829		37.29	1197
Faroe Islands	38,439	7114	18.50724525		18.68	7180
Federated States of Micronesia	47,068	18,304	38.88841676		38.75	18,239
Fiji	695,821	439,979	63.23163572		62.72	436,444
Finland	4,695,602	444,147	9.45878718		9.77	458,672
France	59,536,588	5,912,627	9.931081371		10.23	6,092,515
French Guiana	165,852	39,053	23.54689723		23.64	39,211

Table 1 (*continued*)

Country	LS 2004 Pop. count	Poverty index Pop./DN of lights	Normalized Poverty index	Pop. at $2	Estimated % pop. in poverty	Pop. in poverty
French Polynesia	188,965	32,107	16.99097717		17.19	32,475
Gabon	1,298,722	497,500	38.30688939		38.18	495,823
Gambia, The	1,530,432	943,096	61.62286204	82.9	61.14	935,695
Gaza Strip	1,215,324	25,997	2.139100355		2.56	31,108
Georgia	4,607,018	1,882,474	40.86100814	25.3	40.69	1,874,735
Germany	82,400,920	6,623,378	8.037990353		8.37	6,896,061
Ghana	20,757,632	11,722,743	56.4743753	78.5	56.07	11,638,610
Gibraltar	2134	40	1.874414246		2.30	49
Greece	10,108,853	911,099	9.012882075		9.33	943,054
Greenland	22,203	5465	24.61379093		24.69	5483
Grenada	80374	11890	14.79334113		15.02	12,073
Guadeloupe	427,219	21,129	4.945707003		5.32	22,744
Guam	153,632	4002	2.604926057		3.02	4637
Guatemala	14,216,922	5,011,455	35.24992963	31.9	35.17	4,999,698
Guernsey	59,942	2027	3.381602215		3.78	2268
Guinea	8,752,494	7,289,555	83.28546126		82.47	7,218,411
Guinea-Bissau	1,373,508	1,116,884	81.3161627		80.53	1,106,131
Guyana	721,281	258,292	35.81017662		35.72	257,634
Haiti	7,235,315	5,742,130	79.3625433	78.0	78.61	5,687,633
Honduras	6,703,436	2,955,525	44.08970265	44.0	43.87	2,940,974
Hungary	10,037,936	925,908	9.224087502	2.0	9.54	957,316
Iceland	196,515	17,579	8.945373127		9.26	18,202
India	1,057,940,160	432,462,048	40.87774189	79.9	40.71	430,682,152
Indonesia	230,437,184	72,962,944	31.66283441	52.4	31.63	72,898,018
Iran	66,679,992	7,417,150	11.12350163	7.3	11.41	7,606,536
Iraq	25,401,568	3,689,061	14.52296567		14.76	3,748,082
Ireland	3,831,847	534,687	13.95376694		14.19	543,922
Israel	5,758,514	133,250	2.313965026		2.73	157,316
Italy	56,361,584	2,565,767	4.552333022		4.94	2,782,142
Jamaica	2,586,471	228,111	8.819391364	13.3	9.14	236,363
Japan	122,212,544	3,996,036	3.269742916		3.67	4,489,041
Jersey	82,118	3343	4.070971042		4.46	3664
Jordan	5,572,494	396,493	7.115180384	7.0	7.46	415,715
Kazakhstan	15,179,085	4,969,387	32.73838311	16.0	32.69	4,962,629
Kenya	32,995,200	24,951,860	75.62269663	58.3	74.93	24,722,093
Kiribati	17,333	17,290	99.75191831		98.69	17,106
Kuwait	1,890,507	30,938	1.636492221		2.06	39,034
Kyrgyzstan	5,075,365	1,166,264	22.97891876	21.4	23.08	1,171,533
Laos	6,058,058	4,928,035	81.34677813	74.1	80.56	4,880,578
Latvia	2,223,746	731,451	32.89274045	4.7	32.85	730,409
Lebanon	3,417,654	149,416	4.371887851		4.76	162,630
Lesotho	1,849,655	1,395,481	75.44547497	56.1	74.75	1,382,650
Liberia	3,300,648	2,850,279	86.3551339		85.50	2,821,910
Libya	5,551,676	270,569	4.873645364		5.25	291,611
Liechtenstein	34,288	1070	3.120625292		3.53	1209
Lithuania	3,630,869	1,085,065	29.88444364	7.8	29.88	1,085,023
Luxembourg	462,770	22,114	4.778615727		5.16	23,875
Macau	335,964	5345	1.590944268		2.02	6786
Macedonia	2,041,607	294,820	14.44058528	2.0	14.67	299,589
Madagascar	17,327,632	15,237,829	87.93947725	85.1	87.06	15,084,725
Malawi	11,926,030	9,708,824	81.40868336	76.1	80.62	9,615,287
Malaysia	22,533,766	3,455,715	15.33571885	9.3	15.56	3,505,289
Maldives	7302	6918	94.7411668		93.75	6846
Mali	11,991,182	9,530,089	79.47580981	90.6	78.72	9,439,564
Malta	395,953	6921	1.74793473		2.17	8610
Man, Isle of	68,780	5144	7.47891829		7.82	5377
Marshall Islands	2721	2721	100		98.93	2692
Martinique	413,127	10,495	2.540381045		2.95	12,207
Mauritania	2,985,837	1,976,208	66.18606441	63.1	65.63	1,959,698
Mauritius	1,202,791	95,080	7.904947742		8.24	99,085
Mayotte	166,760	43,925	26.34024946		26.39	44,013
Mexico	103,642,488	14,185,453	13.68690898	20.4	13.93	14,439,438
Moldova	4,414,398	1,530,652	34.6740824	63.7	34.60	1,527,388
Monaco	37,648	659	1.750424989		2.18	820
Mongolia	2,750,697	1,556,653	56.59122033	74.9	56.18	1,545,455
Montenegro	631,295	160,196	25.37577519		25.44	160,621
Montserrat	7442	2277	30.59661381		30.58	2276
Morocco	30,762,500	11,551,969	37.55211377	14.3	37.43	11,515,764
Mozambique	19,011,130	15,199,992	79.9531222	78.4	79.19	15,055,092
Myanmar (Burma)	42,042,736	32,736,268	77.86426649		77.13	32,429,172
Namibia	1,954,033	1,201,780	61.50254371	55.8	61.02	1,192,367
Nauru	6292	1063	16.89446917		17.09	1075
Nepal	27,324,488	20,323,872	74.37969926	68.5	73.70	20,138,756
Netherlands	16,173,456	617,607	3.818645811		4.21	681,501

Table 1 (*continued*)

Country	LS 2004 Pop. count	Poverty index Pop./DN of lights	Normalized Poverty index	Pop. at $2	Estimated % pop. in poverty	Pop. in poverty
Netherlands Antilles	214,734	7097	3.305019233		3.71	7962
New Caledonia	188,719	91,825	48.65699797		48.37	91,284
New Zealand	3,710,020	659,783	17.78381249		17.97	666,564
Nicaragua	5,326,395	2,441,418	45.83621755	79.9	45.59	2,428,442
Niger	11,358,765	9,428,276	83.00441113	85.8	82.20	9,336,433
Nigeria	125,230,200	74,172,360	59.22881222	92.4	58.78	73,612,358
Niue	1987	1519	76.44690488		75.74	1505
Norfolk Island	1166	398	34.13379074		34.07	397
North Korea	22,118,370	14,522,741	65.65918284		65.11	14,402,214
Northern Mariana Islands	73,311	2648	3.612009112		4.01	2940
Norway	3,874,556	509,637	13.15342971		13.41	519,446
Oman	2,779,827	228,708	8.227418469		8.56	237,827
Pacific Islands (Palau)	17,398	5595	32.15886884		32.12	5589
Pakistan	150,458,480	30,951,944	20.57175109	73.6	20.71	31,163,202
Panama	2,947,302	805,433	27.32780692	17.1	27.37	806,545
Papua New Guinea	4,982,047	4,145,149	83.20172411		82.39	4,104,716
Paraguay	6,192,809	2,057,807	33.22897574	33.2	33.18	2,054,588
Peru	27,107,278	10,312,459	38.04313734	31.8	37.92	10,278,533
Philippines	80,894,936	32,367,210	40.01141678	47.5	39.86	32,241,763
Pitcairn Islands	12	12	100		98.93	12
Poland	38,532,904	4,328,540	11.23336045	2.0	11.52	4,437,339
Portugal	10,287,886	1,066,204	10.36368405	2.0	10.66	1,096,612
Puerto Rico	3,776,725	104,236	2.75995737		3.17	119,764
Qatar	790,184	15,543	1.967010215		2.39	18,887
Reunion	734,280	36,162	4.924824318		5.30	38,939
Romania	22,340,994	3,914,299	17.52070208	12.9	17.71	3,956,029
Russia	136,951,264	27,412,296	20.01609565	12.1	20.16	27,616,155
Rwanda	8,260,457	7,196,167	87.11584601	83.7	86.24	7,124,213
San Marino	27,657	579	2.093502549		2.51	696
Sao Tome and Principe	168,051	81,981	48.78340504		48.49	81,496
Saudi Arabia	25,296,724	745,425	2.946725434		3.36	848,714
Senegal	10,835,367	6,259,861	57.77248708	63.0	57.35	6,213,806
Serbia	10,157,930	1,548,864	15.247831		15.47	1,571,347
Seychelles	73,966	5490	7.422329178		7.76	5742
Sierra Leone	5,797,537	4,451,654	76.78526243	74.5	76.07	4,410,257
Singapore	4,056,963	64,572	1.591633939		2.02	81,973
Slovakia	5,444,300	579,040	10.63571074	2.9	10.93	594,907
Slovenia	2,015,106	236,329	11.7278694	2.0	12.00	241,867
Solomon Islands	300,258	296,622	98.78904142		97.74	293,474
Somalia	8,070,147	6,388,557	79.16283309		78.41	6,328,017
South Africa	46,178,680	15,860,874	34.34674616	34.1	34.28	15,829,024
South Korea	46,351,628	1,272,533	2.745390086	2.0	3.16	1,463,210
Spain	39,345,568	3,587,082	9.116864192		9.43	3,710,833
Sri Lanka	19,673,058	5,562,245	28.27341331	41.6	28.30	5,566,838
St. Helena	6406	3819	59.61598501		59.16	3790
St. Kitts and Nevis	31,492	2019	6.411152039		6.77	2131
St. Lucia	160,294	14,015	8.743309169		9.06	14,528
St. Pierre and Miquelon	6165	702	11.38686131		11.67	719
St. Vincent and the Grenadines	85,957	11,658	13.56259525		13.81	11,870
Sudan	40,477,684	28,385,708	70.12680864		69.51	28,137,650
Suriname	436,395	75,040	17.19543075		17.39	75,877
Swaziland	1,162,306	772,012	66.42071881		65.86	765,544
Sweden	8,422,661	694,997	8.251513388		8.58	722,596
Switzerland	7,495,454	316,764	4.226081569		4.61	345,911
Syria	17,519,194	2,524,654	14.41078853		14.64	2,565,659
Taiwan	22,422,116	563,246	2.512010909		2.93	656,279
Tajikistan	7,016,487	1,902,822	27.11929773	42.8	27.16	1,905,691
Tanzania	35,682,252	30,005,020	84.08947955	89.9	83.26	29,710,620
Thailand	64,282,796	25,207,240	39.21304232	25.2	39.07	25,115,355
Togo	5,504,241	3,958,939	71.92524819		71.29	3,923,703
Tokelau	19	19	100		98.93	19
Tonga	67,818	30,181	44.50293432		44.28	30,030
Trinidad and Tobago	948,415	46,424	4.894903602	39.0	5.27	50,016
Tunisia	9,594,410	2,050,932	21.37632225	6.6	21.50	2,063,230
Turkey	66,611,716	16,278,926	24.4385327	18.7	24.52	16,333,304
Turkmenistan	4,902,287	1,011,539	20.63402245		20.77	1,018,376
Turks and Caicos Islands	12,079	3099	25.65609736		25.72	3107
Tuvalu	2282	855	37.46713409		37.35	852
UAE	2,337,453	40,892	1.74942555		2.18	50,861
Uganda	26,510,656	22,554,436	85.07686871		84.24	22,331,728
Ukraine	47,394,232	11,581,390	24.43628583	4.9	24.52	11,620,096
United Kingdom	58,968,480	2,707,626	4.591649641		4.97	2,933,656
United States	283,670,530	16,198,668	5.710380983		6.08	17,237,759
Uruguay	3,373,244	404,426	11.98923054	5.7	12.26	413,563

Table 1 (*continued*)

Country	LS 2004	Poverty index	Normalized	Pop. at $2	Estimated % pop. in poverty	Pop. in poverty
	Pop. count	Pop./DN of lights	Poverty index			
Uzbekistan	26,394,720	3,817,477	14.46303276		14.70	3,879,046
Vanuatu	149,687	130,655	87.28546901		86.41	129,347
Venezuela	24,298,028	2,502,267	10.29823079	27.6	10.59	2,574,327
Vietnam	81,340,168	30,049,828	36.94340538		36.83	29,961,623
Virgin Islands	95,919	2692	2.80653468		3.22	3086
Wallis and Futuna	13,860	12,312	88.83116883		87.93	12,188
West Bank	2,618,904	109,979	4.199428463		4.59	120,174
Western Sahara	263,076	30,467	11.58106403		11.86	31,196
Western Samoa	145,152	87,024	59.9537037		59.50	86,359
Yemen	19,738,336	11,580,185	58.66849668	45.2	58.23	11,493,601
Zambia	11,124,310	7,541,083	67.78922019	94.1	67.21	7,476,863
Zimbabwe	12,654,553	8,463,353	66.87990481	83.0	66.32	8,392,048

Table 2
Decadal classes of national poverty level estimates for 81 countries having populations in excess of 10 M.

Poverty level (%)	Countries
1–10	Taiwan, S. Korea, Egypt, Saudi Arabia, Japan, Belgium, Netherlands, Italy, United Kingdom, USA, Canada, Czech Republic, Germany, Greece, Spain, Hungary, France
11–20	Venezuela, Portugal, Iran, Poland, Australia, Mexico, Syria, Uzbekistan, Iraq, Serbia, Malaysia, Argentina, Chile, Romania, Russia
21–30	Algeria, Pakistan, Colombia, Ukraine, Turkey, Brazil, Ecuador, Sri Lanka
31–40	Byelarus, Indonesia, Kazakhstan, Cuba, South Africa, Guatemala, Vietnam, Morocco, Peru, Thailand, Philippines
41–50	India, China
51–60	Bangladesh, Cote d'Ivoire, Ghana, Senegal, Yemen, Nigeria
61–70	North Korea, Zimbabwe, Zambia, Cameroon, Sudan
71–80	Nepal, Kenya, Angola, Myanmar, Congo DRC, Mali, Mozambique, Afghanistan
81–90	Malawi, Niger, Tanzania, Uganda, Cambodia, Madagascar, Burkina Faso, Ethiopia

Several of the observational shortcomings of the OLS will be addressed by the low-light imaging data that will be acquired with the Visible Infrared Imaging Radiometer Suite (VIIRS) which will fly on the National Polar-Orbiting Environmental Satellite System (NPOESS) during the next decade. The VIIRS low-light imaging sensor will continue to acquire night global data, but will have on-board calibration and at higher spatial resolution (0.8 km) than the OLS. Thus, it can be expected that poverty assessments made with VIIRS data will be of higher quality than those that can be achieved with the OLS.

In total, OLS lighting was not detected for 1.68 billion people. While the OLS is remarkable for its detection of dim lighting, it is clear that the quality of the poverty index could be improved through the detection of even dimmer lighting. The VIIRS instrument is designed to match the detection limits achieved by the OLS. In addition, both the OLS and VIIRS will only acquire low-light imaging data in a single broad visible/near-infrared band. There is spectral information on the type of lighting and changes in the type of lighting could be quite useful for improving the quality of poverty estimates. The final area where a substantial improvement in low-light imaging could be envisioned is in spatial resolution. Recent simulations made with high spatial resolution airborne camera imagery of nighttime lights (Elvidge et al., 2007) indicate that the optimal resolution for global collections of nighttime lights data would be approximately 50 m.

Past efforts at estimating poverty levels have relied only on household surveys conducted by individual governments. Inconsistencies in the sampling structures, nature and timing of the surveys, and differing definitions of poverty makes the assembly of a globally consistent spatially disaggregated poverty map an impossibility with the survey data alone. Our results indicate that a new class of poverty maps can be developed based on global satellite-based measures of economic activity calibrated based on survey data. It can be anticipated that improvements in global poverty mapping will occur over time through the use of nation-specific calibrations, inclusion of improved reference data (poverty levels and/or economic data) and as improvements are made in population density grids and satellite observation of human activities related to economic activity and technology access.

5. Conclusion

The eradication of poverty is an important human objective for myriad moral and practical reasons. Improvements in our ability to map and perhaps monitor poverty are vital for increasing our understanding of the causes and nature of poverty, and, for the development and assessment of poverty-eradication policies. The expense in time and money associated with household surveys is often an impediment to the acquisition of needed poverty information. This research contributes to a growing body of literature that suggests that satellite imagery can significantly enhance our knowledge of the socio-economic conditions of humanity at increasingly fine spatial resolution around the world. Clearly we are not there yet, and much research needs to be done with respect to increasing our ability to have satellite imagery and on the ground survey information mutually inform each other to enable improved intelligent interpolation. Nonetheless, this very simple exercise using relatively simple population counts from LandScan (informed by both survey data and satellite imagery) divided by a relatively simple measure of emitted nocturnal lights (the DMSP–OLS satellite imagery), produces poverty indices that correlate very strongly with other accepted measures at national and sub-national levels. More work along the lines of CIESIN's Poverty Mapping Project that uses geo-referenced household survey information in tandem with satellite imagery and derivative data products has the potential to dramatically improve the spatial and temporal accuracy of our knowledge of the socio-economic conditions of humanity.

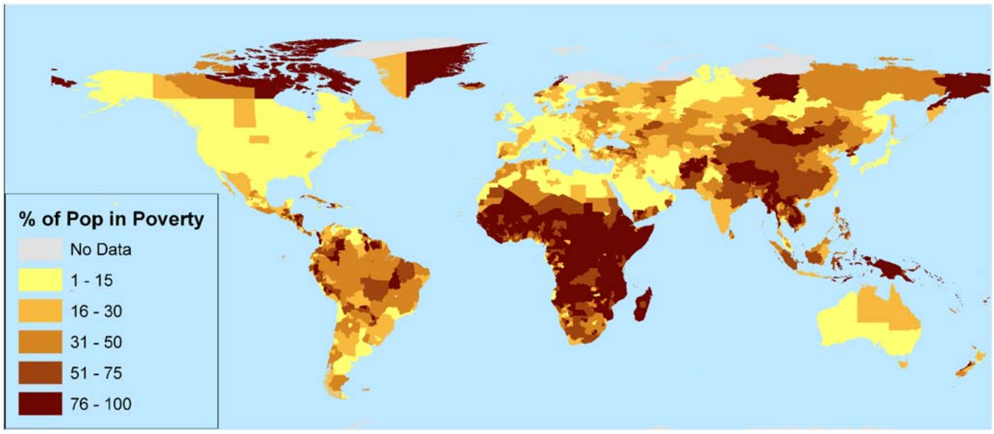

Fig. 4. Map of poverty levels for 2543 sub-national administrative units estimated based on satellite data-derived poverty index.

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