A Global Poverty Map Derived From Satellite Data

Christopher D. Elvidge [a]
Paul S. Sutton [b]
Kimberly E. Baugh [c]
Benjamin T. Tuttle [c,b]
Ara T. Howard [c]
Edward H. Erwin [a]
Budhendra Bhaduri [d]
Edward Bright [d]

[a] U.S. Department of Commerce, NOAA National Geophysical Data Center, 325 Broadway, Boulder, Colorado 80205 USA (chris.elvidge@noaa.gov)
[b] Department of Geography, University of Denver, Denver, Colorado 80208 USA (psutton@du.edu).
[c] Cooperative Institute for Research in the Environmental Sciences, University of Colorado, Boulder, Colorado, USA
[d] U.S. Department of Energy, Oak Ridge National Laboratory, Oak Ridge, Tennessee 37831 USA

Submitted to AMBIO December 27, 2006.

A Global Poverty Map Derived From Satellite Data

Abstract

A global poverty map has been produced at 30 arc second 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 2.3 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.

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 closely associated with environmental degradation (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 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 either $1 or $2 per day (Figure 1).

Place Figure 1 near here.

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). 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 and $2 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 et al., 2000 and 2001, Henninger and Snel, 2002 and 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, 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 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 socioeconomic measures such as population density, living conditions, and economic activity. In this paper we present the first spatially disaggregated global map of poverty numbers derived from satellite data from four distinct sensor types. 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 an 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 arc second grid and two grids are produced with no data sources in common. Since the nighttime lights product has a latitudinal extent of 65 south to 65 north, this determined the extent of the analysis. This results in a truncation of administrative units that straddle the 65 degree north latitude line and the small number of administrative units located entirely above this line have not been included in the anlysis. Below is a description of the two data sources.

2.1 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. The basic concept of the LandScan data sets is to perform a spatial allocation of census reported population numbers based on model developed with spatially disaggregated data. The term population count is used instead of population density - which 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 affect 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 Controlled Image Base (CIB) from the U.S. National Geospatial Intelligence Agency (NGA).

2.2 Nighttime Lights

The U.S. Air Force Defense Meteorological Satellite Program (DMSP) Opeartional 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 pm to 10 pm range local time.

With a swath width of 3000 km and fourteen orbits per day, each OLS instrument is capable of generating a complete coverage of nighttime data in a twenty-four hour 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 to 0.9 µm) and the thermal band pass covers the 10.5 to 12.5 µm region. DMSP-OLS is basically designed for global observation of cloud cover. At night, the visible band is intensified with a photo-multiplier 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 watts/cm2/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 including Elvidge et al., 1997, Sutton et al. 2001 and 2006, Doll et al., 2000, and Ebeners et al., 2005. 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 and Calibration

The poverty index (PI) 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 grayscale image that is adjusted to lower values in abundantly lit areas where economic activity is high (Figure 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.

Place Figure 2 near here.

A calibration for estimating the number of people living in poverty was developed based on the World Development Indicators 2006 national level estimates for the percentage of people living on $2 or less per day. To establish the calibration, the sum 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 Figure 3).

Place Figure 3 near here.

3. Results

The calibration from Figure 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_global_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 232 countries to generate national poverty levels and poverty counts, which are presented in Table 1. Among the eighty countries having populations greater than ten million those having poverty rate estimates greater than 80% are Ethiopia, Burkina Faso, Madagascar, Cambodia, Uganda, Tanzania, 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, and the USA.

Place Table 1 near here.

Place Table 2 near here.

The procedure used to generate the national level poverty estimates was then applied at sub-national level for 2,543 administrative units having LandScan population values above zero. These results are presented graphically in Figure 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.

5. 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 2.3 billion, consistent with the 2.6 billion estimated by the World Bank (2006).

Since the resulting poverty data set is at 30 arc second 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 arc second level has not been assessed.

The poverty estimate for Egypt of 6.7% 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 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.

Several of the observational shortcomings of the OLS will be addressed by the low light imaging data that will be acquired with the VIIRS (Visible Infrared Imaging Radiometer Suite) which will fly on the NPOESS (National Polar Orbiting Environmental Satellite System) during the next decade. The VIIRS low light imaging sensor will continue to acquire nightly global data, but will have onboard 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., 2006) indicates that the optimal resolution for global collections of nighttime lights data would be approximately 50 meters.

Past efforts at estimating poverty levels have relied 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.

Acknowledgments

This study was funded in part by the NASA carbon cycle research program.

References

Balk, D., Pozzi, F., Yetman, G., Deichmann, U. and Nelson, A. The distribution of people and the dimension of place: Methodologies to improve the global estimation of urban extent. Proceedings of the Urban Remote Sensing Conference, Tempe, Arizona, April 2005.

Bhaduri, B., Bright, E., Coleman, P., Dobson, J. LandScan: Locating people is what matters. Geoinformatics 2002; 5; 34-37.

CIESIN (Center for International Earth Science Information Network). Where the Poor Are: An Atlas of Poverty. Columbia University: Palisades, New York; 2006.

De Navas-Walt, C., Proctor, B.D., Lee, C.H. Income, Poverty, and Health Insurance Coverage in the United States: 2004. U.S. Census Bureau, Current Population Reports, P60-229, Government Printing Office: Washington, DC; 2005.

Dobson, J., Bright, E.A., Coleman, P.R., Durfee, R.C. and Worley., B.A. LandScan: a global population database for estimating populations at risk. Photogrammetric Engineering and Remote Sensing 2000; 66; 849–857.

Doll, C.N.H., Muller, J.-P. and Elvidge, C.D. Night-time imagery as a tool for global mapping of socio-economic parameters and greenhouse gas emissions. Ambio; 2000; 29; 157–162.

Ebener, S., Murray, C., Tandon, A. and Elvidge, C. From wealth to health: modeling the distribution of income per capita at the sub-national level using nighttime lights imagery. International Journal of Health Geographics 2005; 4; 5–14.

Elvidge, C. D., Baugh, K.E., Dietz, J.B., Bland, T., Sutton, P.C. and Kroehl, H.W. Radiance calibration of DMSP-OLS low-light imaging data of human settlements. Remote Sensing of Environment 1999; 68; 77–88.

Elvidge, C.D., Imhoff, M.L., Baugh, K.E., Hobson, V.R., Nelson, I., Safran, J., Dietz, J.B. and Tuttle, B.T. Night-time lights of the world: 1994–1995. ISPRS Journal of Photogrammetry & Remote Sensing 2000;56; 81–99.

Elvidge, C.D., Cinzano, P., Pettit, D.R., Arvesen, J., Sutton, P., Small, C., Nemani, R., Longcore, T., Rich, C. The Nightsat mission concept. Submitted to the International Journal of Remote Sensing 2006.

Friedl, M.A., McIver, D.K., Hodges, J.C.F., Zhang, X.Y., Muchoney, D., Strahler, A.H., Woodcock, C.E., Gopal, S., Schneider, A., Cooper, A., Baccini, A., Gao, F., Schaaf, C. Global land cover mapping from MODIS: algorithms and early results, Remote Sensing of Environment 2002; 83; 287-302.

Henninger N. Mapping and Geographic Analysis of Human Welfare and Poverty-Review Assessment. World Resources Institute, Washington D.C.; 1998.

Henninger, N. and Snel, M. Where are the Poor: Experiences with the Development and Use of Poverty Maps. World Resources Institute, Washington, D.C.; 2002.

Hentschel, J. and Lanjouw, P. Using disaggregated poverty maps to plan sectoral investments. PremNotes No. 5, The World Bank, Washington, D.C.; 1998.

Karshenas, M. Global Poverty Estimates and the Millennium Goals: Towards a Unified Framework. International Labour Office, Employment Strategy Papers; 2004; 5.

Rodriguez, E., C.S. Morris, J.E. Belz, E.C. Chapin, J.M. Martin, W. Daffer, S. Hensley, An Assessment of the SRTM Topographic Products, Technical Report JPL D-31639, Jet Propulsion Laboratory, Pasadena, California; 2005.

Sachs J.D, A new map of the world. Economist magazine 2000; 24; 81-83.

Sachs J.D., Mellinger A.D. & Gallup J.L. The geography of poverty and wealth. Scientific American 2001; March; 70-75.

Sachs, J.D. The End of Poverty: Economic Possibilities of Our Time. Penguin Group: New York; 2005.

Snel, M. Poverty-Conservation Mapping Applications. IUCN World Conservation Congress, November 17-25, 2004.

Small, C., Pozzi, F. and C. Elvidge, C. Spatial analysis of global urban extent from DMSP-OLS night lights. Remote Sensing of Environment 2005; 96; 277–291.

Sutton, P.C., Roberts, D., Elvidge, C. and Baugh, K. Census from heaven: an estimate of the global population using nighttime satellite imagery. International Journal of Remote Sensing 2000; 22; 3061–3076.

Sutton, P.C., Ghosh, T., Elvidge, C.D. Estimation of gross domestic product at sub-national scales using nighttime satellite imagery. Submitted to the International Journal of Ecological Economics and Statistics 2006.

World Bank. World Development Indicators. Washington, D.C.; 2006.

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

Country	LandScan 2004 Pop. Count	Poverty Index Pop. / DN of lights	Normalized Pov. Index	Pop. @ $2	% of Pop. In Poverty	Pop. Count In Poverty
Afghanistan	28,410,980	22,720,812	79.97		78.22	22,222,917
Albania	3,433,109	1,048,854	30.55	11.8	32.35	1,110,638
Algeria	31,545,580	6,488,516	20.57	15.1	23.09	7,282,559
American Samoa	52,085	6,103	11.72		14.87	7,745
Andorra	69,962	2,508	3.58		7.32	5,123
Angola	10,645,932	8,116,065	76.24		74.75	7,958,082
Anguilla	12,639	886	7.01		10.50	1,327
Antigua and Barbuda	65,157	4,034	6.19		9.74	6,347
Argentina	38,696,260	6,155,672	15.91	14.3	18.76	7,259,344
Armenia	2,997,641	745,416	24.87	49.0	27.07	811,610
Aruba	67,267	1,401	2.08		5.93	3,988
Australia	19,322,928	2,434,531	12.60		15.69	3,031,597
Austria	8,129,847	641,930	7.90		11.32	920,620
Azerbaijan	7,755,703	2,241,748	28.90	9.1	30.82	2,390,502
Bahamas, The	272,594	28,337	10.40		13.64	37,192
Bahrain	600,058	10,023	1.67		5.55	33,278
Bangladesh	140,576,752	74,129,376	52.73	82.8	52.94	74,418,083
Barbados	268,632	9,591	3.57		7.31	19,635
Belgium	10,365,412	365,976	3.53		7.27	753,822
Belize	207,691	85,576	41.20		42.24	87,724
Benin	7,293,065	4,880,697	66.92		66.11	4,821,292
Bermuda	25,489	763	2.99		6.77	1,727
Bhutan	2,089,054	1,743,478	83.46		81.45	1,701,634
Bolivia	8,722,603	3,112,077	35.68	34.3	37.11	3,236,909
Bosnia and Herzegovina	3,992,185	962,210	24.10		26.37	1,052,559
Botswana	1,646,061	907,605	55.14	55.7	55.17	908,139
Brazil	178,096,304	47,004,832	26.39	22.4	28.49	50,742,208
British Virgin Islands	18,734	1,895	10.12		13.38	2,507
Brunei	289,717	13,669	4.72		8.37	24,262
Bulgaria	7,496,528	1,123,072	14.98	16.2	17.90	1,341,875
Burkina Faso	13,545,902	12,137,364	89.60	81.0	87.16	11,806,219
Burundi	6,366,676	5,948,226	93.43	87.6	90.71	5,775,079
Byelarus	10,324,346	3,194,345	30.94	2.0	32.71	3,377,261
Cambodia	13,380,562	11,578,787	86.53	77.7	84.31	11,281,184
Cameroon	16,022,772	11,071,732	69.10	50.6	68.13	10,916,143
Canada	32,018,318	2,248,726	7.02		10.51	3,366,392
Cape Verde	362,955	135,551	37.35		38.66	140,310
Cayman Islands	26,487	1,601	6.04		9.61	2,544
Central African Republic	3,722,174	3,005,653	80.75	84.0	78.94	2,938,342
Chad	9,567,083	8,219,044	85.91		83.73	8,010,554
Chile	15,210,395	2,470,981	16.25	9.6	19.07	2,901,111
China	1,270,484,096	555,786,560	43.75	46.7	44.60	566,601,687
Cocos (Keeling) Islands	248	248	100.00		96.81	240

Colombia	41,348,352	9,982,628	24.14	22.6	26.40	10,917,202
Comoros	588,444	483,929	82.24		80.32	472,658
Congo	3,045,933	1,341,775	44.05		44.88	1,367,035
Congo, DRC	57,911,408	45,987,808	79.41		77.70	44,996,291
Cook Islands	14,069	4,731	33.63		35.21	4,953
Costa Rica	3,873,384	683,451	17.64	9.5	20.37	789,089
Cote d'Ivoire	16,304,796	9,032,927	55.40	38.4	55.41	9,035,145
Croatia	4,346,473	540,639	12.44	2.0	15.54	675,444
Cuba	11,114,198	3,717,823	33.45		35.04	3,894,673
Cyprus	748,246	46,350	6.19		9.74	72,915
Czech Republic	10,234,140	740,201	7.23	2.0	10.71	1,095,904
Denmark	5,262,941	608,894	11.57		14.73	775,411
Djibouti	188,692	100,749	53.39		53.55	101,047
Dominica	34,830	16,638	47.77		48.33	16,834
Dominican Republic	8,696,280	1,460,172	16.79	2.0	19.58	1,702,682
East Timor	1,004,007	877,431	87.39		85.11	854,481
Ecuador	12,734,118	3,378,047	26.53	40.8	28.62	3,644,042
Egypt	75,099,408	2,155,994	2.87	43.9	6.66	5,001,631
El Salvador	6,549,989	1,426,553	21.78	58.0	24.21	1,585,725
Equatorial Guinea	422,433	278,467	65.92		65.18	275,331
Eritrea	4,401,247	3,442,824	78.22		76.60	3,371,223
Estonia	1,306,149	321,127	24.59	5.2	26.81	350,233
Ethiopia	71,440,984	64,750,296	90.63	77.8	88.12	62,950,802
Falkland Islands (Islas Malvinas)	3,211	1,201	37.40		38.71	1,243
Faroe Islands	38,439	7,114	18.51		21.17	8,139
Federated States of Micronesia	47,068	18,304	38.89		40.09	18,869
Fiji	695,821	439,979	63.23		62.68	436,157
Finland	4,695,602	444,147	9.46		12.77	599,837
France	59,536,588	5,912,627	9.93		13.21	7,866,444
French Guiana	165,852	39,053	23.55		25.85	42,873
French Polynesia	188,965	32,107	16.99		19.77	37,349
Gabon	1,298,722	497,500	38.31		39.55	513,633
Gambia, The	1,530,432	943,096	61.62	84.0	61.19	936,460
Gaza Strip	1,215,324	25,997	2.14		5.98	72,687
Georgia	4,607,018	1,882,474	40.86	15.7	41.92	1,931,245
Germany	82,400,920	6,623,378	8.04		11.46	9,439,655
Ghana	20,757,632	11,722,743	56.47	78.5	56.41	11,709,544
Gibraltar	2,134	40	1.87		5.74	122
Greece	10,108,853	911,099	9.01		12.36	1,249,513
Greenland	22,203	5,465	24.61		26.84	5,959
Grenada	80,374	11,890	14.79		17.73	14,247
Guadeloupe	427,219	21,129	4.95		8.59	36,680
Guam	153,632	4,002	2.60		6.41	9,853
Guatemala	14,216,922	5,011,455	35.25	37.4	36.71	5,219,295
Guernsey	59,942	2,027	3.38		7.13	4,276
Guinea	8,752,494	7,289,555	83.29		81.29	7,115,325
Guinea-Bissau	1,373,508	1,116,884	81.32		79.47	1,091,487
Guyana	721,281	258,292	35.81		37.23	268,546
Haiti	7,235,315	5,742,130	79.36		77.65	5,618,502
Honduras	6,703,436	2,955,525	44.09	44.0	44.92	3,010,933

Hungary	10,037,936	925,908	9.22	2.0	12.56	1,260,424
Iceland	196,515	17,579	8.95		12.30	24,167
India	1,057,940,160	432,462,048	40.88	80.6	41.94	443,648,912
Indonesia	230,437,184	72,962,944	31.66	52.4	33.38	76,925,864
Iran	66,679,992	7,417,150	11.12	7.3	14.32	9,548,244
Iraq	25,401,568	3,689,061	14.52		17.47	4,438,831
Ireland	3,831,847	534,687	13.95		16.95	649,358
Israel	5,758,514	133,250	2.31		6.14	353,754
Italy	56,361,584	2,565,767	4.55		8.22	4,633,282
Jamaica	2,586,471	228,111	8.82	13.3	12.18	315,058
Japan	122,212,544	3,996,036	3.27		7.03	8,591,827
Jersey	82,118	3,343	4.07		7.77	6,384
Jordan	5,572,494	396,493	7.12	7.4	10.60	590,644
Kazakhstan	15,179,085	4,969,387	32.74	24.9	34.38	5,218,694
Kenya	32,995,200	24,951,860	75.62	58.3	74.18	24,476,772
Kiribati	17,333	17,290	99.75		96.58	16,740
Kuwait	1,890,507	30,938	1.64		5.51	104,250
Kyrgyzstan	5,075,365	1,166,264	22.98	24.7	25.32	1,285,225
Laos	6,058,058	4,928,035	81.35	73.2	79.50	4,815,883
Latvia	2,223,746	731,451	32.89	8.3	34.52	767,728
Lebanon	3,417,654	149,416	4.37		8.05	275,229
Lesotho	1,849,655	1,395,481	75.45	56.1	74.02	1,369,084
Liberia	3,300,648	2,850,279	86.36		84.14	2,777,293
Libya	5,551,676	270,569	4.87		8.52	472,939
Liechtenstein	34,288	1,070	3.12		6.89	2,363
Lithuania	3,630,869	1,085,065	29.88	6.9	31.73	1,152,148
Luxembourg	462,770	22,114	4.78		8.43	39,015
Macau	335,964	5,345	1.59		5.47	18,384
Macedonia	2,041,607	294,820	14.44	4.0	17.40	355,202
Madagascar	17,327,632	15,237,829	87.94	85.1	85.61	14,834,938
Malawi	11,926,030	9,708,824	81.41	76.1	79.55	9,487,508
Malaysia	22,533,766	3,455,715	15.34	9.3	18.23	4,107,673
Maldives	7,302	6,918	94.74		91.93	6,713
Mali	11,991,182	9,530,089	79.48	90.6	77.76	9,324,223
Malta	395,953	6,921	1.75		5.62	22,244
Man, Isle of	68,780	5,144	7.48		10.94	7,522
Marshall Islands	2,721	2,721	100.00		96.81	2,634
Martinique	413,127	10,495	2.54		6.35	26,247
Mauritania	2,985,837	1,976,208	66.19	63.1	65.42	1,953,467
Mauritius	1,202,791	95,080	7.90		11.33	136,304
Mayotte	166,760	43,925	26.34		28.44	47,431
Mexico	103,642,488	14,185,453	13.69	26.3	16.70	17,306,914
Moldova	4,414,398	1,530,652	34.67	64.1	36.18	1,597,014
Monaco	37,648	659	1.75		5.62	2,116
Mongolia	2,750,697	1,556,653	56.59	74.9	56.52	1,554,673
Montenegro	631,295	160,196	25.38		27.55	173,905
Montserrat	7,442	2,277	30.60		32.39	2,411
Morocco	30,762,500	11,551,969	37.55	14.3	38.85	11,950,789
Mozambique	19,011,130	15,199,992	79.95	78.4	78.20	14,867,084
Myanmar (Burma)	42,042,736	32,736,268	77.86	78.4	76.26	32,063,171

Namibia	1,954,033	1,201,780	61.50	55.8	61.08	1,193,476
Nauru	6,292	1,063	16.89		19.68	1,238
Nepal	27,324,488	20,323,872	74.38	80.9	73.03	19,954,846
Netherlands	16,173,456	617,607	3.82		7.54	1,219,427
Netherlands Antilles	214,734	7,097	3.31		7.06	15,167
New Caledonia	188,719	91,825	48.66		49.16	92,765
New Zealand	3,710,020	659,783	17.78		20.50	760,595
Nicaragua	5,326,395	2,441,418	45.84	79.9	46.54	2,478,758
Niger	11,358,765	9,428,276	83.00	85.8	81.03	9,204,459
Nigeria	125,230,200	74,172,360	59.23	90.8	58.97	73,844,805
Niue	1,987	1,519	76.45		74.95	1,489
Norfolk Island	1,166	398	34.13		35.68	416
North Korea	22,118,370	14,522,741	65.66		64.94	14,362,661
Northern Mariana Islands	73,311	2,648	3.61		7.35	5,387
Norway	3,874,556	509,637	13.15		16.20	627,815
Oman	2,779,827	228,708	8.23		11.63	323,338
Pacific Islands (Palau)	17,398	5,595	32.16		33.84	5,888
Pakistan	150,458,480	30,951,944	20.57	65.6	23.09	34,738,849
Panama	2,947,302	805,433	27.33	17.6	29.36	865,302
Papua New Guinea	4,982,047	4,145,149	83.20		81.22	4,046,275
Paraguay	6,192,809	2,057,807	33.23	33.2	34.84	2,157,336
Peru	27,107,278	10,312,459	38.04	37.7	39.30	10,654,324
Philippines	80,894,936	32,367,210	40.01	47.5	41.13	33,272,980
Pitcairn Islands	12	12	100.00		96.81	12
Poland	38,532,904	4,328,540	11.23	2.0	14.42	5,557,010
Portugal	10,287,886	1,066,204	10.36	2.0	13.61	1,400,623
Puerto Rico	3,776,725	104,236	2.76		6.56	247,643
Qatar	790,184	15,543	1.97		5.82	45,998
Reunion	734,280	36,162	4.92		8.57	62,901
Romania	22,340,994	3,914,299	17.52	14.0	20.26	4,525,594
Russia	136,951,264	27,412,296	20.02	7.5	22.57	30,913,932
Rwanda	8,260,457	7,196,167	87.12	83.7	84.85	7,008,990
San Marino	27,657	579	2.09		5.94	1,642
Sao Tome and Principe	168,051	81,981	48.78		49.27	82,803
Saudi Arabia	25,296,724	745,425	2.95		6.73	1,702,579
Senegal	10,835,367	6,259,861	57.77	63.0	57.62	6,242,862
Serbia	10,157,930	1,548,864	15.25		18.15	1,843,400
Seychelles	73,966	5,490	7.42		10.88	8,051
Sierra Leone	5,797,537	4,451,654	76.79	74.5	75.26	4,363,333
Singapore	4,056,963	64,572	1.59		5.47	222,027
Slovakia	5,444,300	579,040	10.64	2.9	13.87	754,949
Slovenia	2,015,106	236,329	11.73	2.0	14.88	299,856
Solomon Islands	300,258	296,622	98.79		95.68	287,299
Somalia	8,070,147	6,388,557	79.16		77.47	6,251,823
South Africa	46,178,680	15,860,874	34.35	34.1	35.87	16,565,946
South Korea	46,351,628	1,272,533	2.75	2.0	6.54	3,033,051
Spain	39,345,568	3,587,082	9.12		12.46	4,901,314
Sri Lanka	19,673,058	5,562,245	28.27	50.7	30.24	5,948,497
St. Helena	6,406	3,819	59.62		59.33	3,800
St. Kitts and Nevis	31,492	2,019	6.41		9.95	3,132

St. Lucia	160,294	14,015	8.74		12.11	19,412
St. Pierre and Miquelon	6,165	702	11.39		14.56	898
St. Vincent and the Grenadines	85,957	11,658	13.56		16.58	14,254
Sudan	40,477,684	28,385,708	70.13		69.08	27,962,775
Suriname	436,395	75,040	17.20		19.96	87,083
Swaziland	1,162,306	772,012	66.42	22.5	65.64	762,964
Sweden	8,422,661	694,997	8.25		11.65	981,572
Switzerland	7,495,454	316,764	4.23		7.92	593,478
Syria	17,519,194	2,524,654	14.41		17.37	3,043,175
Taiwan	22,422,116	563,246	2.51		6.33	1,418,639
Tajikistan	7,016,487	1,902,822	27.12	42.8	29.17	2,046,401
Tanzania	35,682,252	30,005,020	84.09	72.5	82.04	29,274,098
Thailand	64,282,796	25,207,240	39.21	32.5	40.39	25,963,893
Togo	5,504,241	3,958,939	71.93		70.75	3,894,313
Tokelau	19	19	100.00		96.81	18
Tonga	67,818	30,181	44.50		45.30	30,721
Trinidad and Tobago	948,415	46,424	4.89	20.0	8.54	80,981
Tunisia	9,594,410	2,050,932	21.38	6.6	23.84	2,286,866
Turkey	66,611,716	16,278,926	24.44	10.3	26.68	17,770,353
Turkmenistan	4,902,287	1,011,539	20.63	44.0	23.15	1,134,706
Turks and Caicos Islands	12,079	3,099	25.66		27.81	3,359
Tuvalu	2,282	855	37.47		38.77	885
UAE	2,337,453	40,892	1.75		5.62	131,346
Uganda	26,510,656	22,554,436	85.08	96.6	82.96	21,992,572
Ukraine	47,394,232	11,581,390	24.44	45.7	26.68	12,642,617
United Kingdom	58,968,480	2,707,626	4.59		8.26	4,869,103
United States	283,670,530	16,198,668	5.71		9.30	26,368,455
Uruguay	3,373,244	404,426	11.99	3.9	15.12	510,136
Uzbekistan	26,394,720	3,817,477	14.46	71.7	17.42	4,597,698
Vanuatu	149,687	130,655	87.29		85.01	127,245
Venezuela	24,298,028	2,502,267	10.30	30.6	13.55	3,293,245
Vietnam	81,340,168	30,049,828	36.94	33.4	38.28	31,139,948
Virgin Islands	95,919	2,692	2.81		6.60	6,331
Wallis and Futuna	13,860	12,312	88.83		86.44	11,981
West Bank	2,618,904	109,979	4.20		7.89	206,713
Western Sahara	263,076	30,467	11.58		14.74	38,788
Western Samoa	145,152	87,024	59.95		59.64	86,569
Yemen	19,738,336	11,580,185	58.67	45.2	58.45	11,536,506
Zambia	11,124,310	7,541,083	67.79	87.4	66.91	7,443,541
Zimbabwe	12,654,553	8,463,353	66.88	83.0	66.07	8,360,663
Global Poverty Estimate						2,306,971,576

Table 2
Decadal Classes of National Poverty Level Estimates for The Eighty Countries Having Populations in Excess of Ten Million

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

List of Figures

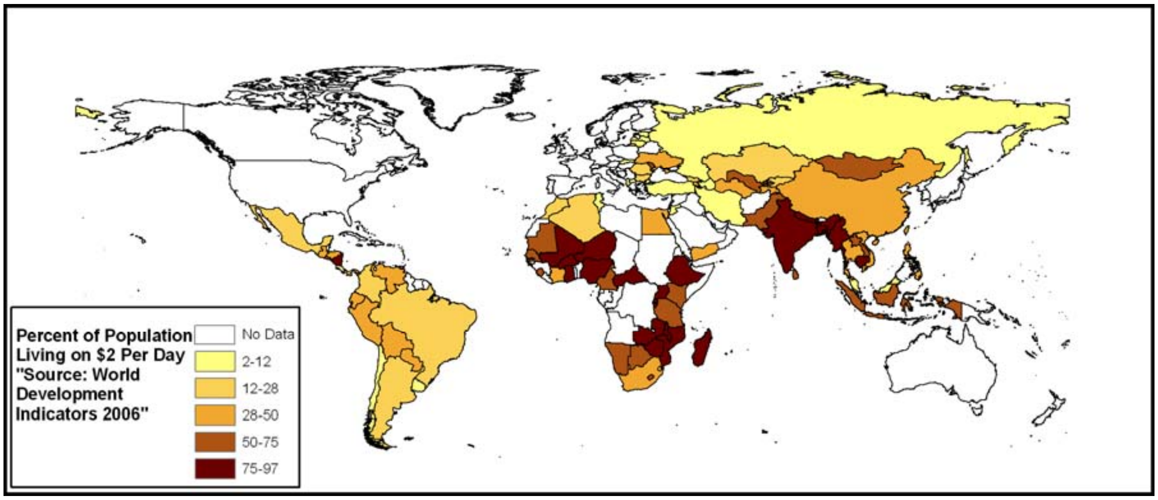

Figure 1. Map of poverty levels for countries reporting international poverty line data (percent of population living on $2 per day or less) from the World Development Indicators 2006. Note that a number of countries have no data reported and that the $2 per day poverty line is not applicable to developed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

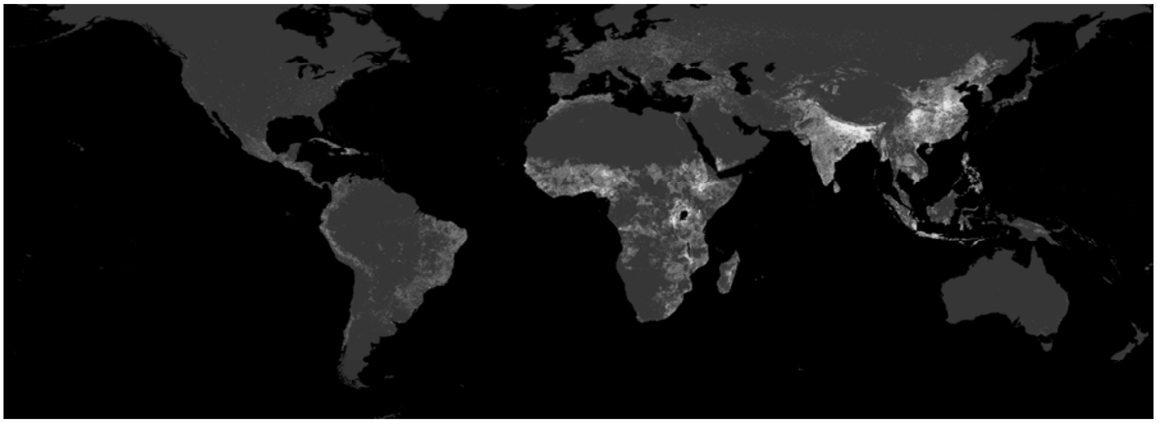

Figure 2. Poverty index calculated by dividing the LandScan 2004 population count by the average digital number of the DMSP satellite F15 nighttime lights from 2003.

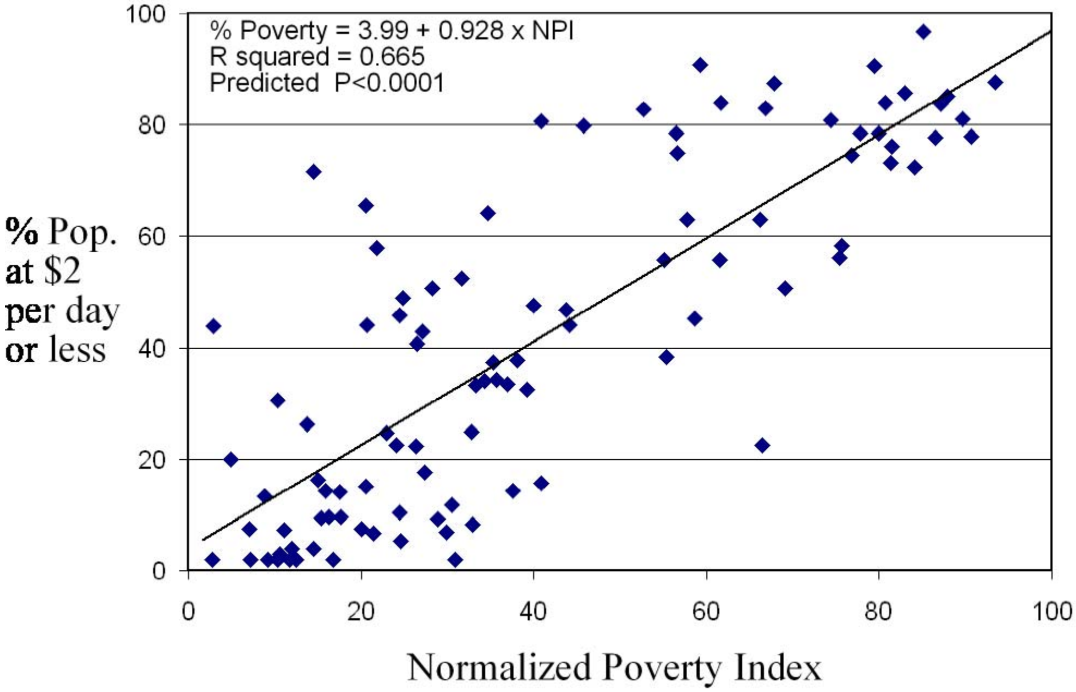

Figure 3. Calibration of the Normalized Poverty Index (NPI) for estimation of poverty levels.

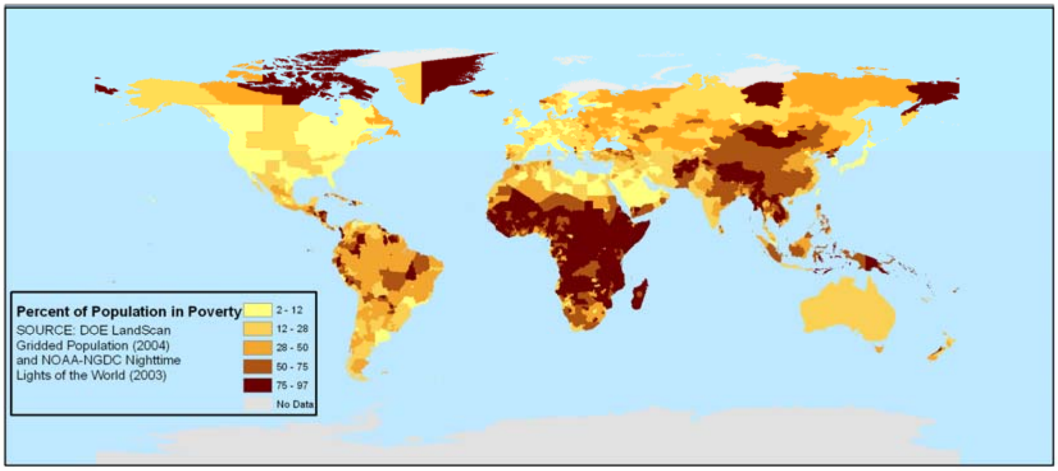

Figure 4. Map of poverty levels for 2543 sub-national administrative units estimated based on the satellite data derived poverty index.