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The Night Light Development Index (NLDI): a spatially explicit measure of human development from satellite data

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Abstract. We have developed a satellite data derived "Night Light Development Index" (NLDI) as a simple, objective, spatially explicit and globally available empirical measurement of human development derived solely from nighttime satellite imagery and population density. There is increasing recognition that the distribution of wealth and income amongst the population in a nation or region correlates strongly with both the overall happiness of that population and the environmental quality of that nation or region. Measuring the distribution of wealth and income at national and regional scales is an interesting and challenging problem. Gini coefficients derived from Lorenz curves are a well-established method of measuring income distribution. Nonetheless, there are many shortcomings of the Gini coefficient as a measure of income or wealth distribution. Gini coefficients are typically calculated using national level data on the distribution of income through the population. Such data are not available for many countries and the results are generally limited to single values representing entire countries. In this paper we develop an index for the co-distribution of nocturnal light and people that is derived without the use of monetary measures of wealth and is capable of providing a spatial depiction of differences in development within countries.

1 Introduction

Nocturnal lighting is one of the hallmarks of our technological society. The cores of modern cities are bathed in light at night and nocturnal lighting can be used to define the spatial extent of development. Since 1994 our group has been producing satellite derived maps of nighttime lights using low light imaging data collected by the US Air Force Defence Meteorological Satellite Program (DMSP). Recently we conducted a study of electrification rates by overlaying DMSP nighttime lights and gridded population data. We found the number of people living in areas with no detectable lighting to be highly correlated to reported electrification rates (Elvidge et al., 2011). During the course of this study we noticed an interesting pattern in scattergrams plotting population count versus the brightness of satellite observed lighting. In extremely poor countries the scattergram points are aligned along the population axis with very little spread on the lighting axis (Fig. 1 – Bangladesh), indicating a dearth of outdoor lighting. In contrast, on scattergrams of economically developed countries with lower population densities, the data cloud forms a circular pattern pressed against the axes near the origin (Fig. 2 – United States). The scattergrams for developing countries retain the alignment of points with the population axis, but with a wider range of lighting levels (Fig. 3 – China). Figures 1 and 2 appeared to be end members for a continuum of scattergram patterns that relate to development levels. As development advances lighting is added and grid cells will move outward, away from the population axis. We imagined that the development level

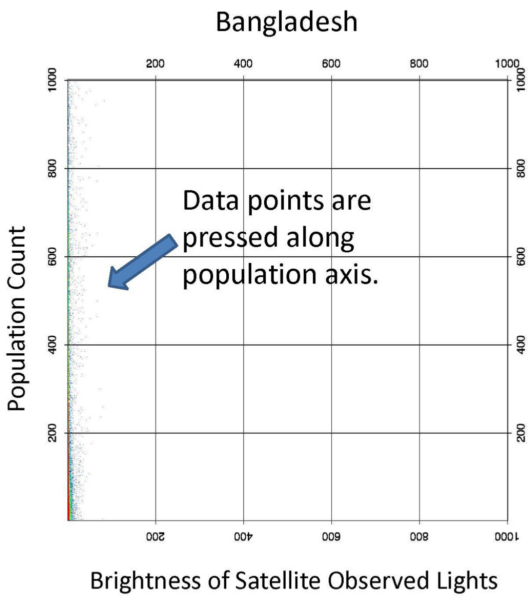

Figure 1. Scattergram of population versus the brightness of satellite observed lighting for Bangladesh in 2006. Note that the data points are compressed along the population axis with very little expansion along the lighting axis.

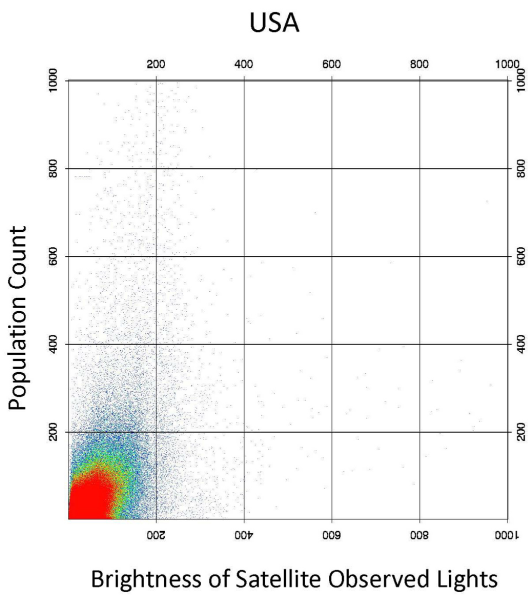

Figure 2. Scattergram of population versus the brightness of satellite observed lighting for USA in 2006. Note that the data cloud has a circular shape and is pressed against both axes at the origin.

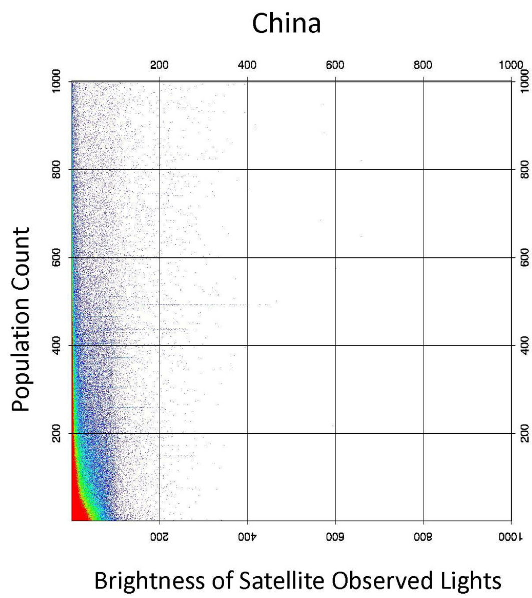

Figure 3. Scattergram of population versus the brightness of satellite observed lighting for China in 2006. Note that the data points are aligned along the population axis with evidence of expansion along the lighting axis.

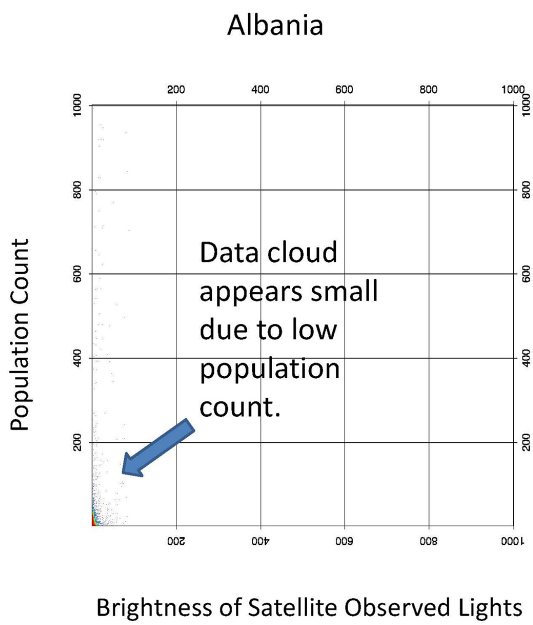

Figure 4. Scattergram of population versus the brightness of satellite observed lighting for Albania in 2006. Same scale as Figs. 1–3. Note that the data cloud appears similar to that of China, but appears quite small and close to the origin due to the smaller population number.

of countries could be rated based on their scattergram patterns. We recognized that extracting the patterns from the scattergrams would require a normalization process to account for differences in population size and areal extent of nations (Fig. 4 – Albania).

After reviewing literature on normalization procedures, we concluded that the co-distribution of nocturnal light and people could be analyzed following the procedure developed to derive Gini coefficients (Gini, 1936). This method

10 km x 10 km Population Grid

0	0	0	0	0	0	0	0	0	0
0	0	1	1	2	1	2	1	4	1
1	1	3	2	3	4	4	4	3	1
1	1	4	5	5	5	10	5	5	2
1	2	5	5	10	10	10	10	10	3
1	3	5	5	10	30	50	30	10	4
2	2	5	10	10	50	100	50	10	10
15	5	5	5	10	30	50	30	10	3
4	3	5	5	10	10	10	10	10	2
0	2	5	5	5	5	10	5	5	1

10 km x 10 km DMSP OLS Image

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	2	0	0	0
0	0	0	0	2	2	10	1	2	0
0	0	0	0	2	50	150	50	5	0
0	0	0	0	10	150	255	150	10	2
5	0	0	0	2	50	150	50	5	0
0	0	0	0	0	5	10	5	2	0
0	0	0	0	0	0	0	0	0	0

Analysis of the population grid relative to the light grid (above) produces a table that contrasts % of Population to % of light in any given country or area (See table below).

Light Level (DN)	Pop in DN	Cum % of Light	Cum % of Pop
0	205	0.0	25.0
1	10	0.1	26.2
2	90	1.5	37.2
5	55	3.7	43.9
10	40	7.2	48.8
50	120	24.8	63.4
150	200	77.6	87.8
255	100	100.0	100.0

Total Pop = 820 Total Light = 1137

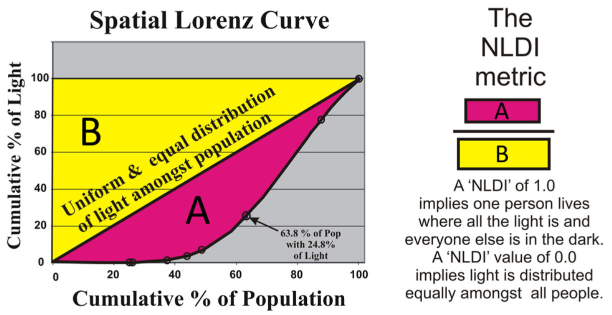

Figure 5. A graphical representation of the Gini coefficient. The coefficient is calculated as the area between the Lorenz curve and the diagonal divided by the area above the diagonal.

yields a numerical value that is independent of population size. The Gini coefficient is widely used to measure the dispersion of a variable across a population, region, or nation. The most common use of the Gini coefficient is to measure the degree of inequality in the distribution of annual income across a population. The index is calculated from the Lorenz curve (Lorenz, 1905), in which cumulative income is plotted against cumulative population arranged from the poorest to the richest (Fig. 5). It is aspatial because it aggregates income categories regardless of where they are located. The diagonal line at 45 degrees represents perfect equality of incomes. Disparities in income pull the line into a concave curve, as shown in Fig. 5. The labels A and B are missing, colors have been used. The labels A and B need to be incorporated in the figures. The Gini coefficient is the ratio of the area that lies between the curve and the diagonal divided by the total area above the line of equality: Gini = A/B. As income disparity increases the size of "A" increases, driving the ratio to higher values. Gini coefficient values range from 0 (equality in distribution) to 1.

The Gini coefficient has been used for many years and corresponds with many existing stereotypical ideas of political economy. For example, Scandinavian countries such as Norway, Sweden, Finland, and Denmark have lower Gini coefficients which represent broader distributions of income. Brazil and Mexico have historically had relatively high Gini coefficients although Mexico's has been dropping significantly in the last few decades. The Gini coefficients of China, India, the United States, and the United Kingdom have been increasing in the last few decades. In fact, if current trends continue the Gini coefficient of the United States will surpass that of Mexico. This international comparison demonstrates some of the strengths of the Gini coefficient. It is scale-independent and population-independent (large nations can be compared to small nations and large economies can be compared to small economies), and it still functions in correct ways when money is transferred (if measured income is transferred from the rich to the poor, the Gini coefficient responds appropriately by decreasing).

Both the World Bank and the US Central Intelligence Agency have programs that analyze government reported income distribution data to produce national level income Gini coefficients. There are several limitations to these data. First, there is no systematic program to collect the required data in a consistent manner and on a repeated timetable. There is no way to determine how much of the variation in income Gini coefficient values is attributable to differences in data collection methods between countries. Also, there are quite a few countries where the available data are insufficient for the calculation of Gini coefficients (Fig. 6). In addition, the data for many countries is quite dated, in some cases more than a decade old (Fig. 7). Finally, the national level granularity of the data masks the variation in income distribution that exists within a country.

Four recent studies (Sutton et al., 2007; Henderson et al., 2009; Ghosh et al., 2010 and Chen and Nordhaus, 2011) made use of satellite observed nighttime lights to model the spatial distribution of gross domestic product (GDP). These studies developed correlations between the brightness of nocturnal lighting and economic activity levels. The approach takes advantage of the fact that global satellite maps of lighting can be produced in a consistent, repeatable manner on an annual basis. Given the successful use of satellite observed nighttime lights in the spatial mapping of economic activity, would it be possible to estimate disparities in income distribution by combining the nighttime lights with gridded population data? To address this question we have developed the Night Light Development Index (NLDI), applying the Lorenz curve analysis to characterize the co-distribution of nocturnal lighting and people. We derive NLDI at a range of spatial aggregations and investigate its meaning through comparison to the traditional income

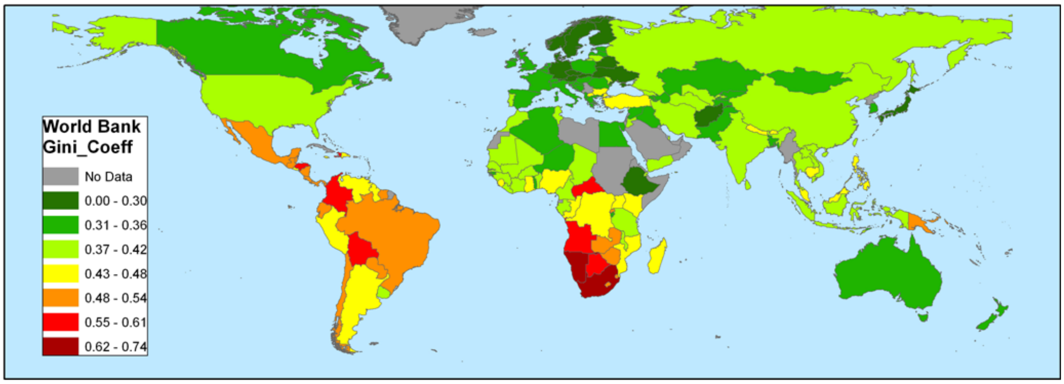

Figure 6. Map of national income Gini coefficients reported by the World Bank.

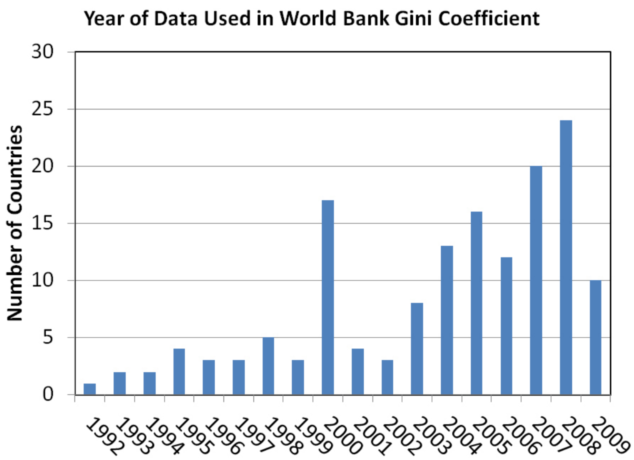

Figure 7. Due to the lack of a systematic international data collection system, the data used to calculate income Gini coefficients span nearly two decades.

Gini coefficient, the Human Development Index (HDI) and a series of other variables.

2 Methods

The inputs for traditional Gini coefficients are in tabular form, derived from population and income statistics. To form the NLDI, the inputs are also in tabular form, but drawn from global geospatial grids of nighttime lights and population. It is important that the two grids be on the same map projection, with a common spatial resolution, and that the features are spatially coregistered. For the nighttime lights we used the year 2006 radiance lights derived from the US Air Force Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS). This data set is a cloud-free composite, incorporating data acquired from low, medium, and high gain setting to overcome the limited dynamic range of the OLS sensor (Ziskin et al., 2010). The methods described by Baugh et al. (2010) were used to remove lighting associated with ephemeral fires and zero out the values in areas with no detected lighting. The digital values in the product can be multiplied by a coefficient to convert to radiances (Watts $\mathrm{cm}^{-2}\,\mathrm{sr}^{-1}$). The data are in a Plate-Carree map projection with a 30 arc second grid spacing. At the equator the grid cell is nearly one kilometre on a side.

For population, we used the year 2006 Landscan grid (Dobson et al., 2000, 2003; Bhaduri et al., 2002). These data are produced in the same 30 arc second Plate-Carree map projection as the nighttime lights. Note that these two data sets were derived independently. The only input data they have in common is digital elevation data, used to perform the terrain correction in the geolocation of the nighttime lights and as one of the variables for modelling population count in the Landscan. That is to say, nighttime lights are not used as an input to the 2006 Landscan data product.

Prior to extraction, the nighttime lights are shifted to obtain the best possible match to the population features. Then lighting from gas flares was masked out (along with associated population) based on gas flare identification from a previous study (Elvidge et al., 2009). The extraction generates a tabular list of the population count and the lighting radiance for all grid cells having either a population count or light detected. The tabular list is then sorted from dimmest to brightest. The Lorenz curves are formed and then the NLDI values are calculated using the same formula as the Gini index.

NLDI coefficients were calculated for the following sets of spatial features:

1. Global – all countries combined.

2. National – a single NLDI value derived for each country.

3. Subnational – NLDI values derived for each state or province inside of individual countries.

4. Gridded – NLDI values derived on a quarter degree grid – with no consideration of national or subnational boundaries.

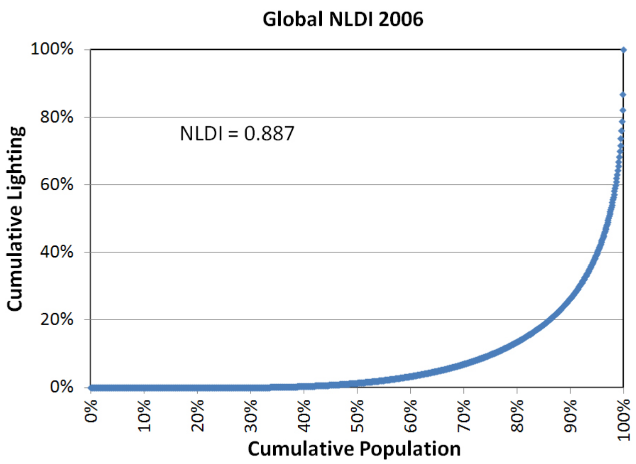

Figure 8. The Lorenz curve for the global NLDI, formed by combining the data from all countries.

We investigated the meaning of the NLDI by determining its correlation with a wide range of national level indices, including the income Gini coefficient (World Bank, 2010), electrification rates (International Energy Agency, 2010), Human Development Index (World Bank, 2010), Human Security Index (www.humansecurityindex.org), percent urban (World Bank), GDP per capita (World Bank, 2010), percent living on $2 or less per day (World Bank, 2010), multidimensional poverty index (World Bank, 2010), ecological footprint (Global Footprint Network, 2010), total primary energy consumption per person (DOE Energy Information Administration, 2010), and electric power consumption per person (DOE EIA, 2010).

3 Results

3.1 The global NLDI

The global NLDI is 0.893. Figure 8 shows the Lorenz curve. Note that the NLDI value is driven to higher values by the 1.2 billion people who live in areas with no detectable lighting (Elvidge et al., 2011).

3.2 National NLDI

At the national level, there is a wide range in the NLDI values. Figure 9 shows results from six countries showing the range of variation obtained with this approach: Afghanistan = 0.921, Brazil = 0.728, Burundi = 0.981, China = 0.791, Sweden = 0.613, and United States = 0.542. Appendix A presents a list of NLDI scores for the countries of the world. Figure 10 shows a global map of national NLDI values. Note that the highly developed countries have low NLDI values and the less and least developed countries have high values. Island states also tend to have unusually low NLDI values.

3.3 Subnational NLDI

The NLDI was calculated for 4550 subnational units, primarily states and provinces (Fig. 11). At this level of aggregation it is possible to see variation within individual countries, such as in China. Urbanized and industrialized eastern Chinese states have much lower NLDI values than the less developed western Chinese states. The same patterns can be seen in the states of India. The developed areas around Bangalore, Hyderabad, Mumbai, and Delhi have lower NLDI scores than more rural interior areas between Delhi and Kolkata. The full set of results are available from the url listed in the acknowledgments.

3.4 Gridded NLDI

The NLDI values can also be calculated on a uniform grid, without consideration of national or subnational boundaries. The first run we made was at a one degree resolution and appeared too coarse. We then ran at half and quarter degree resolution. The quarter degree resolution results provide good spatial detail revealing the variation in the NLDI values within countries on a uniform spatial grid (Fig. 12).

3.5 Correlation with National Level Indices

The NLDI literally measures the level of equality in the distribution of outdoor lighting. This is not to say that there is an even distribution of wealth or income within the 1×1 km pixels by which this assessment is done. Nonetheless, nocturnal lighting is a proxy measure of economic activity, pavement, and built infrastructure. The question we are asking is: *To what extent can NLDI values be used as a spatially explicit proxy for estimating income Gini coefficients or other variables*? To explore this we examined the correlation between national level NLDI values and other national level reported indices and data.

Figure 13 shows that the NLDI is not correlated to the income Gini. We were not surprised by this because if there was a strong correlation between the income Gini and NLDI, it would suggest that brighter lights in the DMSP imagery corresponded with lower population densities of exclusively wealthier people and we know this is not the case. Brightly lit areas correspond to higher population densities (Sutton et al., 2003) and contain a diverse mix of individual income levels. The Lorenz curve methodology of the income Gini motivated this work; however, the NLDI is really more of a spatially explicit measure of development than it is a measure of the nature of income distribution.

Figure 14 shows the NLDI is inversely correlated to electrification rates with a linear regression R^2 of 0.69. As NLDI values rise electrification rates fall. Small NLDI values suggest that larger fractions of the national population have access to sufficient quantities of electricity to be seen from space at night. While there is some debate as to the priority of electricity as a form of development (Taylor, 2005), it

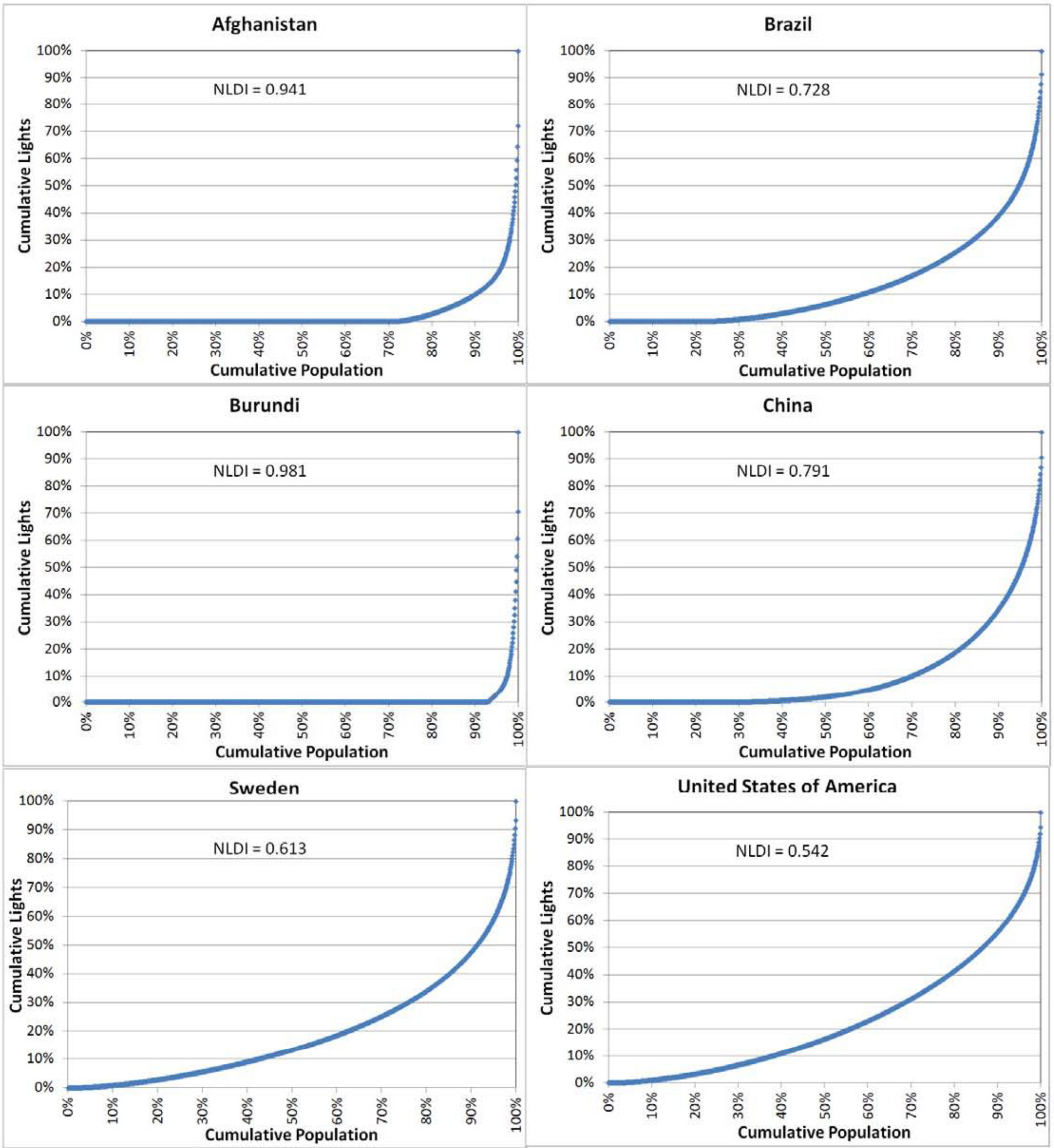

Figure 9. Lorenz curves and NLDI for six countries.

is considered by many to be a significant step in the evolution of a region out of rural poverty.

There is an exponential correlation to both total primary energy consumption per person and electric power consumption per person (Fig. 14). As average per capita energy and electricity consumption levels increase, the NLDI tends to decrease. Electrification often provides public goods, such as outdoor lighting, water pumps, street lights, etc. Again, this proxy measure of the spatial extent of public good provision suggests that NLDI is a measure of broader societal development rather than private income distribution.

The NLDI is inversely correlated to the Human Development Index (HDI), with a linear regression R^2 of 0.71 (Fig. 15). The HDI is an evolving multivariate index intended to capture something akin to "standard of living" (UNDP, 1999). Historically, the HDI was derived from a combination of purchasing power parity, life expectancy, literacy rates, and education levels. Presently, the HDI consists of four ordinal categories: "Very High Human Development", "High Human Development", "Medium Human Development", and "Low Human Development". The NLDI values we have derived for this paper strike us as an interesting surrogate measure of the HDI.

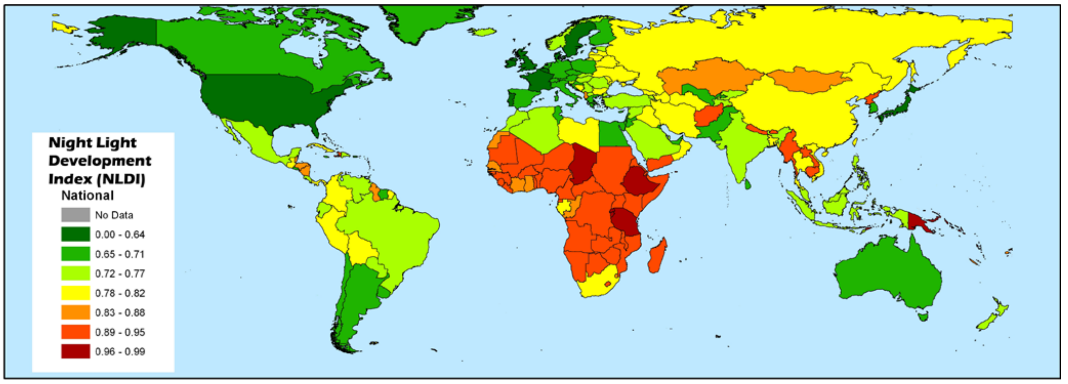

Figure 10. Map of national NLDI values.

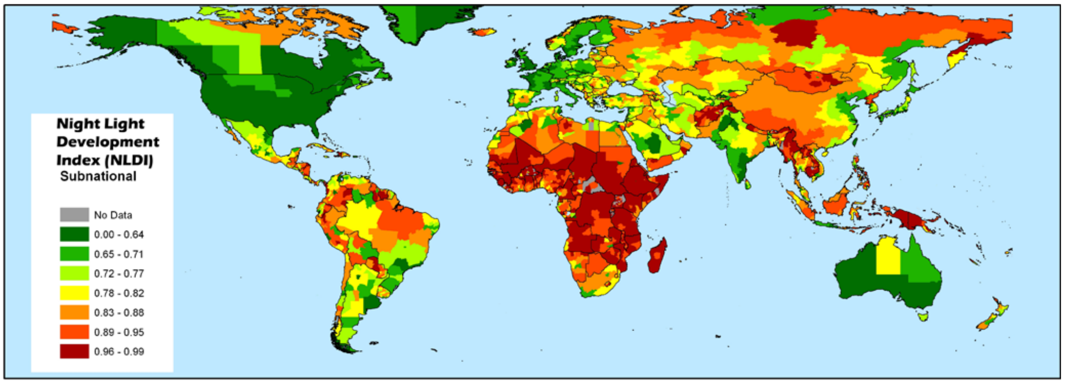

Figure 11. Map of subnational NLDI values.

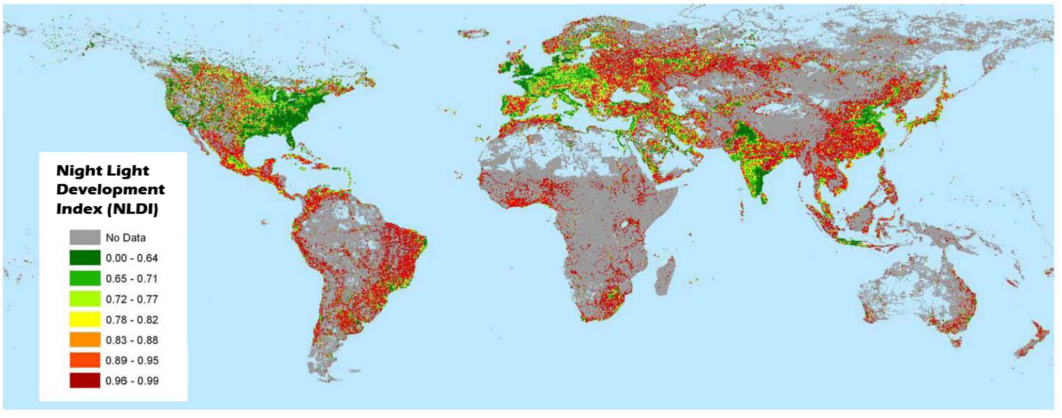

Figure 12. NLDI values produced on a 0.25 degree spatial grid.

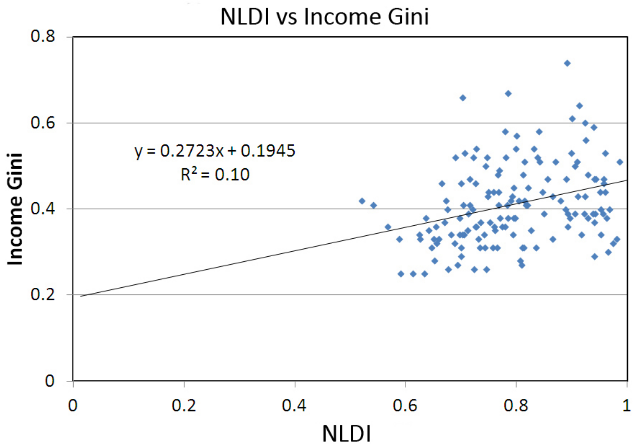

Figure 13. National level NLDI versus Income Gini coefficients. Note the poor correlation, indicating that the two indices are measuring very different phenomena.

The NLDI is slightly less correlated to the Human Security Index (HSI) (Fig. 15). The Human Security Index was developed with less allegiance to a neoclassical economic or neoliberal worldview (Tadjbakhsh and Chenoy, 2006). The HSI is oriented toward measuring political, economic, food, environmental, personal, and community security as opposed to the income, life expectancy, and education variables used by the HDI.

The NLDI is also correlated to the Global Footprint Network's "Ecological Footprint" (Wackernagel and Rees, 1996) (Fig. 15). The ecological footprint is a sophisticated and scalable multivariate measure of the environmental impact of an individual, city, region, or nation. As human development increases as measured by lower NLDI scores so does a nation's ecological footprint.

The NLDI is poorly correlated with the percent of the population living in urban areas (Fig. 16). This finding was surprising because we expected the NLDI to be strongly driven by the large populations that live in "dark" areas of the nighttime imagery which would suggest a stronger correlation between the NLDI and the percent of population in urban areas. However, the weakness of this correlation suggests that the NLDI is actually measuring something quite different from simply the fraction of the population in urban areas. This is consilient with the idea that urbanized does not necessarily imply developed.

The NLDI is positively correlated with the International Poverty Rate (% of population living on $2 per day or less) and the Multidimensional Poverty Index (Fig. 16). This is consilient with the idea that poverty is strongly associated with lack of human development.

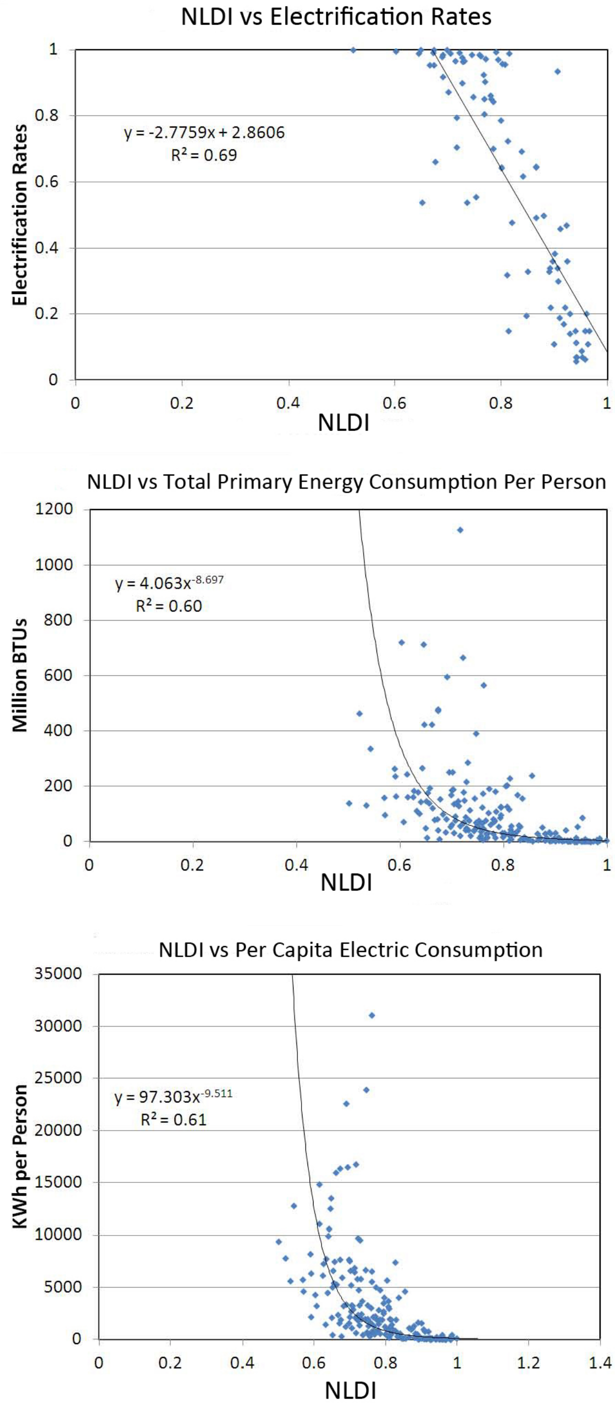

Figure 14. National NLDI's versus electrification rates, total primary energy consumption per person, and electric power consumption per person.

4 Conclusions

The NLDI is an empirical satellite imagery derived metric characterizing the co-distribution of nocturnal lighting and people. It is derived from two spatially explicit datasets that

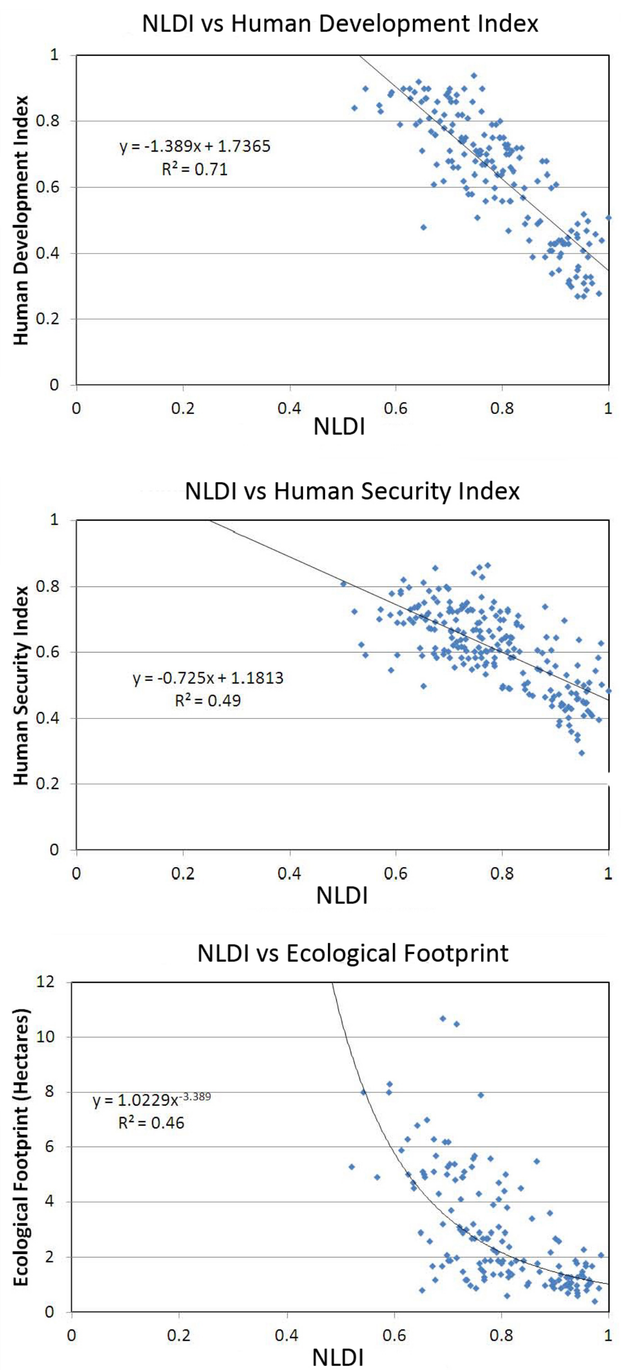

Figure 15. National NLDI's versus the Human Development Index, Human Security Index, and Ecological Footprints.

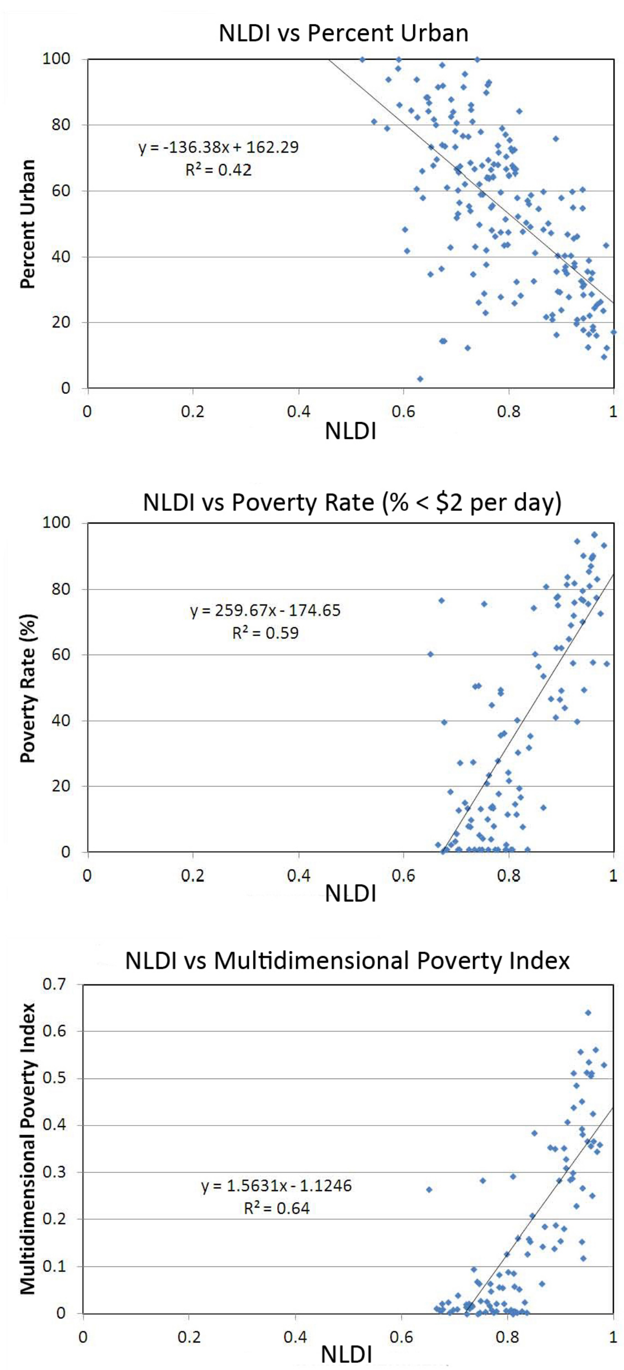

Figure 16. National NLDI's versus the percent urban, poverty index based on the percent living on $2 per day or less, and the multidimensional poverty index.

have global extent: (1) satellite observed nighttime lights of the world, and (2) a population density grid. The two datasets should be on the same map projection and spatial grid. These datasets can be used to produce NLDI values for many differing levels of spatial aggregation including national, subnational, watersheds, or regions. NLDI values can also be produced in a gridded format.

Using national level indices and data we examined the meaning of the NLDI. The strongest correlations were found with the Human Development Index, electrification rates and poverty rates. The NLDI has no correlation to the traditional income Gini. Our conclusion is that the NLDI is a form of development index.

The HDI was developed in 1990 to "to shift the focus of development economics from national income accounting to people centered policies". Several economists, including Mahbub ul Haq and Amartya Sen, spearheaded the effort to develop the HDI with the purpose of shifting the evaluation of development to include improvements in human well-being, such as life expectancy and availability of education (McGillivray and White, 2006). The HDI also has its critics including Bryan Caplan who argues that the HDI merely measures how "Scandinavian your country is" (Caplan, 2009). Another criticism of the HDI stems from uncertainty and errors inherent in the measurements of the data required to generate the HDI (Wolff et al., 2011). Other measures of human well-being attempt to move even further up Maslow's triangle (Maslow, 1943) to include many more facets of existence including creativity, imagination, and intimacy (Max-Neef, 1992). The fact that satellite data can be used to measure an index that is highly correlated, but somewhat different from the HDI, should open up new avenues for research within the socioeconomic research community.

NLDI provides an inexpensive, annually collectable, spatially explicit, and interesting measure of human development in a world that seems to be increasingly less able and/or willing to make social science measurements of phenomena, such as poverty rates, distribution of wealth, and the size and nature of the informal economy. Even in the wealthy United States, there is disturbing talk of eliminating the US Census Bureau's American Community Survey (http://thecaucus.blogs.nytimes.com/2012/05/11/annual-census-at-risk-in-house-budget-bill/). In addition, the construct validity of GDP (as measured in dollars) as a measure of wealth has come under increasing criticism in light of the debt crisis and peak oil. Nocturnal satellite observations of emitted light may prove to be a very simple and increasingly legitimate measure of the spatial distribution of wealth in the near future. We believe that in the future we may have to rely on several inexpensive and uncertain measures of complex phenomena rather than single expensive measures. The benefits of these multiple inexpensive measures are cost of acquisition, standardization in data production, global availability, and robustness of validity.

Acknowledgements. The DMSP data were collected by the US Air Force Weather Agency. The national, subnational and gridded NLDI data for 2006 are available at: http://www.ngdc.noaa.gov/dmsp/download_nldi.html.

Edited by: M. Hannah

Appendix A

National Level NLDI's

Arranged from low to high

COUNTRY NAME	NLDI
Singapore	0.520353
Puerto Rico	0.533734
United States	0.542142
Virgin Is.	0.547139
United Kingdom	0.567949
Malta	0.569789
Belgium	0.588874
Denmark	0.590868
Netherlands Antilles	0.601646
Barbados	0.606124
Sweden	0.61315
Ireland	0.624192
France	0.625508
The Bahamas	0.631705
Japan	0.63415
Portugal	0.63635
Australia	0.64183
Bahrain	0.644723
Luxembourg	0.646397
Lebanon	0.647961
Pakistan	0.650832
Germany	0.651977
Gaza Strip	0.653569
Italy	0.655263
South Korea	0.656316
Canada	0.660235
Cyprus	0.661463
Argentina	0.665317
Uzbekistan	0.670693
Brunei	0.672151
Kuwait	0.672743
Uruguay	0.673295
Sri Lanka	0.675972
Czech Republic	0.677191
Poland	0.681806
Egypt	0.687931
Chile	0.689308
United Arab Emirates	0.690178
Finland	0.693883
Jordan	0.697178
Switzerland	0.697855
Austria	0.699465
Jamaica	0.699792
West Bank	0.699867
Netherlands	0.700503
Greece	0.702717
Tunisia	0.704032

COUNTRY NAME	NLDI
Croatia	0.705547
Suriname	0.706328
Spain	0.711576
Israel	0.713049
French Polynesia	0.714829
El Salvador	0.715822
Qatar	0.716055
Trinidad & Tobago	0.721008
Guadeloupe	0.721884
Mexico	0.721999
Guam	0.722246
Slovakia	0.723256
Malaysia	0.726219
Syria	0.726687
New Zealand	0.727511
Brazil	0.727715
Saudi Arabia	0.729619
Kyrgyzstan	0.73193
Martinique	0.732319
Hungary	0.733825
Indonesia	0.735407
Tajikistan	0.741972
Slovenia	0.743455
Costa Rica	0.743909
Norway	0.745946
Paraguay	0.746465
Serbia & Montenegro	0.747174
Turkey	0.748586
Macedonia	0.74926
India	0.752174
Tonga	0.755326
Mauritius	0.756608
Armenia	0.757864
Venezuela	0.758668
Mayotte	0.759521
Estonia	0.76006
Iceland	0.761126
Algeria	0.761184
Romania	0.765132
Dominican Republic	0.765849
Philippines	0.767564
Morocco	0.767727
Ecuador	0.769006
Iran	0.770696
Bosnia & Herzegovina	0.773575
Colombia	0.779045
Latvia	0.779316
Panama	0.78038
French Guiana	0.782858
Turkmenistan	0.78353
Vietnam	0.783953
South Africa	0.78436
China	0.790197

COUNTRY NAME	NLDI
Azerbaijan	0.793298
Libya	0.793742
Lithuania	0.794403
Bulgaria	0.794687
Moldova	0.797391
Guatemala	0.798685
Bolivia	0.800239
Cuba	0.801556
Russia	0.804115
Ukraine	0.806187
Oman	0.806575
Belarus	0.809833
Bangladesh	0.809955
Peru	0.811753
Iraq	0.8126
Thailand	0.813896
Cape Verde	0.814883
Georgia	0.81736
Gabon	0.819234
Guyana	0.82138
New Caledonia	0.8262
Albania	0.826393
Reunion	0.828527
Western Sahara	0.83182
Belize	0.831961
Kazakhstan	0.835528
Nicaragua	0.837627
Honduras	0.839961
Sao Tome & Principe	0.842297
Congo Brazzaville	0.846647
Senegal	0.849907
The Gambia	0.855559
Mongolia	0.865063
Ghana	0.865703
Swaziland	0.870193
Fiji	0.873962
Cote d'Ivoire	0.879907
Samoa	0.882074
Micronesia	0.882935
Djibouti	0.888333
Nepal	0.889558
Namibia	0.890657
Benin	0.892167
Guinea-Bissau	0.892804
Yemen	0.896662
Lesotho	0.899137
Botswana	0.899713
Mauritania	0.905765
Zimbabwe	0.90578
Sudan	0.906582
Zambia	0.909541
Nigeria	0.910619
Comoros	0.913257

COUNTRY NAME	NLDI
Togo	0.917446
North Korea	0.919889
Cameroon	0.922078
Haiti	0.923155
Sierra Leone	0.924072
Central African Republic	0.924648
Eritrea	0.928301
Kenya	0.929087
Liberia	0.929437
Mali	0.937747
Angola	0.939518
Congo DRC	0.940239
Myanmar	0.940302
Laos	0.940951
Afghanistan	0.940994
Malawi	0.94162
Bhutan	0.942636
Somalia	0.948565
Uganda	0.950379
Equatorial Guinea	0.951899
Niger	0.952176
Burkina Faso	0.952537
Guinea	0.956301
Madagascar	0.95687
Mozambique	0.957835
Cambodia	0.959493
Rwanda	0.960251
Tanzania	0.962704
Ethiopia	0.965819
Chad	0.967964
Timor Leste	0.973773
Vanuatu	0.979758
Burundi	0.980956
Kiribati	0.984707
Papua New Guinea	0.985408
Solomon Is.	0.998823

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