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Census from Heaven: an estimate of the global human population using night-time satellite imagery

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Abstract. Night-time satellite imagery provided by the Defense Meteorological Satellite Program's Operational Linescan System (DMSP OLS) is evaluated as a means of estimating the population of all the cities of the world based on their areal extent in the image. A global night-time image product was registered to a dataset of 2000 known city locations with known populations. A relationship between areal extent and city population discovered by Tobler and Nordbeck is identified on a nation by nation basis to estimate the population of the 22 920 urban clusters that exist in the night-time satellite image. The relationship between city population and city areal extent was derived from 1597 city point locations with known population that landed in a 'lit' area of the image. Due to conurbation, these 1597 cities resulted in only 1383 points of analysis for performing regression. When several cities fell into one 'lit' area their populations were summed. The results of this analysis allow for an estimate of the urban population of every nation of the world. By using the known percent of population in urban areas for every nation a total national population was also estimated. The sum of these estimates is a total estimate of the global human population, which in this case was 6.3 billion. This is fairly close to the generally accepted contemporaneous (1997) estimate of the global population which stood at approximately 5.9 billion.

1. Introduction

The growing human population presents humanity with increasingly difficult challenges with respect to resources; including agricultural production, fresh water stores, loss of biological diversity, diminishing oceanic fish catch, and energy

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production, to name a few (Wilson 1992, Ehrlich 1993, Gleick 1997, Brown *et al.* 1998, Daily *et al.* 1998). In addition, it is expected that the institutional costs associated with meeting these challenges will scale up in non-linear ways (Cincotta and Engelman 1997, Meyerson 1997). Some examples of institutions whose costs do not scale linearly with population size are fisheries management, freshwater infrastructure and management, law enforcement, and public health monitoring agencies (Homer-Dixon 1995, The Trust for Public Lands 1997). Much of global change research is dedicated to discerning naturally induced change from anthropogenically driven change. Understanding many of these social, economic and environmental problems demands accurate information as to the number, spatial distribution and behaviour of human beings on the surface of the planet.

Accurate information as to the size and distribution of the human population is not available for many parts of the world and is of poor quality in many other parts of the world (Clark and Rhind 1992). Official estimates of the population of cities can vary dramatically. For example, the United Nations estimated the population of Mexico City to be 16 million while the US Census Bureau estimated it to be 28 million (Rubenstein 1999). Two estimates of the population of Riyadh, Saudi Arabia are 1.3 million and 3.3 million (Shupe *et al.* 1995, Al-Sahhaf 1998). The present quality of census data is limited and will be increasingly difficult to maintain at current levels due to the growth and increasing mobility of the human population.

Even in the USA, statistical means were considered for estimating sectors of the population that are difficult and expensive to enumerate (Steffey *et al.* 1994). In fact, it is recognized that complete enumeration of the population of the USA is not feasible (Bradburn 1993). The estimated costs of the US census for the year 2000 range from 4 to 4.8 billion dollars, equal to approximately 15 dollars per person (Paez 1997).

Prior to 1992 the Defense Meteorological Satellite Program's Operational Linescan System (DMSP OLS) imagery was produced via analog methods on mylar film. Despite the difficulties associated with quantitatively analysing the mylar media; several researchers used the imagery to demonstrate quantitative relationships between the night-time lights and population and energy utilization for several cities in the USA (Welch 1980, Welch and Zupko 1980). Croft provided an overview of the diverse nocturnal emissions identified by the DMSP OLS (city lights, gas flare burn-off, lantern fishing, forest fires and the aurora borealis) (Croft 1978).

Since 1992 the DMSP OLS data has been available in digital format. The digital format and dramatic strides in computational capability has allowed for production of substantially improved data products. Digital versions of the DMSP OLS imagery have been used to map human settlements globally (Elvidge *et al.* 1997), map urban extent nationally (Imhoff *et al.* 1997), and have been strongly correlated to population and energy consumption at nationally aggregated levels (Elvidge *et al.* 1997). A recently developed dataset that incorporates weighted averages of several gain settings of the satellite ('low-gain' data) shows great promise for not only estimating city populations but actually producing good estimates of the variation of population density within the urban centres (Sutton 1997, Elvidge *et al.* 1998).

This research builds upon these efforts by utilizing these enhanced digital data products to measure the areal extent of the urban areas of the world. Previous research has identified a strong linear relationship between the natural log of a city's areal extent and the natural log of its corresponding population (Stewart and Warntz 1958, Nordbeck 1965, Tobler 1969). We apply this relationship to all the urban areas of the world identified by the DMSP OLS imagery and parametrize the relationship on a national basis. Models of population derived from DMSP OLS data have the potential to provide an inexpensive, easy to update means of mapping the size and spatial distribution of the human population at a global scale.

2. Methods

2.1. *Night-time satellite imagery data*

This paper describes efforts at estimating the population of every country of the world using the stable night-time lights dataset produced from hundreds of orbits from the DMSP OLS (Elvidge *et al.* 1995). The DMSP OLS system consists of a panchromatic visible and near-infrared (VNIR) band and a thermal band. For details on the technical specifications of the DMSP platform see the DMSP user's guide (Dickinson *et al.* 1974). In this study the pixel values are not a measurement of light intensity, but a record of percent of VNIR light observations in a given location. For example, at a given point on the earth's surface, hundreds of DMSP OLS observations are made. If the VNIR sensor saw light at this location on 150 out of 200 nights this pixel would have a value of 75. Consequently the values of the pixels in the image range from 0 to 100. The thermal band is used for screening out cloud-impacted data. The night-time lights dataset used for the analysis was projected in the Interrupted Goode's Homolosine Projection (Steinwand 1994). This projection was used because it is the best global equal-area representation of the lands of the earth. The areal extents of the cities were measured by counting the number of contiguous lit pixels in the image for each isolated urban area.

2.2. *City population data*

The city population data were prepared as a point layer with the city populations attributed to the points. The DMSP OLS night-time city lights image has 22 920 isolated urban areas. This image was superimposed on a point dataset of 1597 cities with known populations. This resulted in 1383 paired {area, population} values to analyse. Each of the paired {area, population} points is referred to as an urban cluster. The conurbation of cities is often reproduced in the night-time satellite image when several city points fall into one 'lit' area. When this occurred the populations of those cities are summed for that urban cluster. The city populations were obtained from both the 1992 United Nations Statistical Yearbook and a 1995 National Geographic Atlas of the world (United Nations 1992, Shupe *et al.* 1995). The city population data included a census date that varied from the 1970s to the 1990s. These city populations were updated to an estimated 1997 value by using nationally and annually specific urban population growth rates (The World Bank 1997). Often city populations were reported both as an administrative value and as a larger metropolitan area value. In all cases the larger metropolitan population value was used.

2.3. *The ln(area) vs ln(population) relationship*

The basic method used to estimate city population is based on the research of Nordbeck and Tobler (Nordbeck 1965, Tobler 1969). This results in a linear relationship between the natural log of cities' areal extent and the natural log of their populations. These methods relate areal extents measured by the night-time satellite imagery with the populations of cities represented as *points* (figure 1). A more accurate relationship has been identified using complete population density images

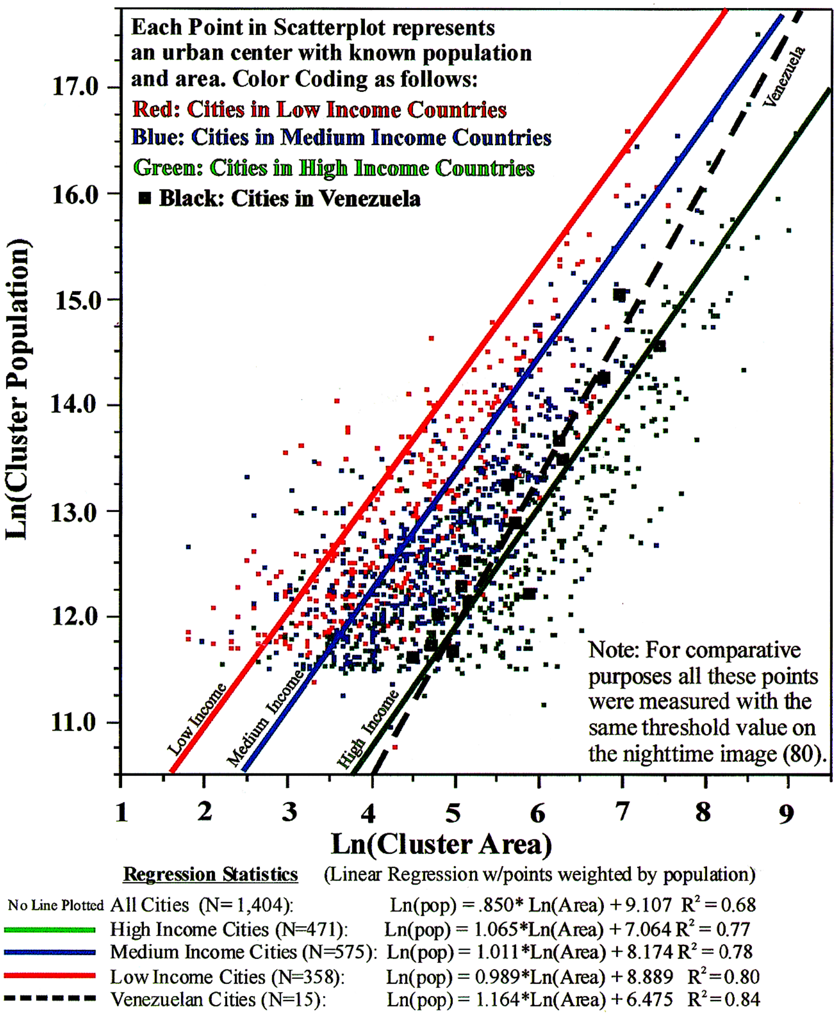

Figure 1. Scatterplot of ln(cluster area) vs ln(cluster population) for all the cities of the world (excluding China) with known population whose areal extent could be measured with the night-time satellite imagery.

(Sutton 1997); however, this method was not used in this investigation because there are no accurate high spatial resolution population density datasets with which to do the analysis for most of the countries of the world. This effort used the best available population data for the cities of the world to identify how the parameters of the ln(area) vs ln(population) relationship vary from nation to nation.

2.4. *Stratification of the DMSP OLS imagery by thresholding*

Thresholding is a process by which the value of the pixels that are analysed in the imagery is controlled on a national basis (i.e. all the pixels in Brazil have the same threshold value). A threshold of 80 for a particular nation would use only those pixels in which light was observed 80% of the time or more. Varying levels of industrialization throughout the world suggest that a single threshold on this dataset would be inappropriate. Setting image thresholds at the national level is trade-off between two conflicting objectives. Low thresholds capture more area and smaller urban clusters that would otherwise not be identified at high thresholds; this approach is generally needed in the less developed countries. Higher thresholds prevent conurbation of urban clusters into mega-clusters that do not lend themselves to accurate population estimates. For example, a low threshold for Japan would produce a huge urban cluster extending from Tokyo, through Nagoya, Osaka and Kyoto, all the way to Kitakyushu (figure 2). Earlier work by Imhoff *et al.* (1997) has shown that a threshold of 84% was a good measure of urban extent within the USA. In an attempt to capture all of the urban population of the world we used three thresholds of 40%, 80% and 90%.

The system for establishing these thresholds worked as follows: Poorer countries with Gross Domestic Product (GDP)/capita less than $1000 per year were assigned thresholds of 40 and the rest of the countries were assigned thresholds of 80. The night-time imagery and the point coverage of cities were then inspected for both extreme conurbation and failure of the imagery to capture large cities. In some cases, such as Egypt, the higher threshold of 90 was applied to prevent conurbation of the cities along most the Nile River. In a few other cases like Germany, the lower threshold of 40 was applied in order to capture large cities. We hope to greatly improve the thresholding process via the use of the low-gain dataset described earlier (Elvidge *et al.* 1998), and more detailed studies on national bases.

2.5. *Estimating the urban and national population of a nation*

The urban and national population of every nation of the world was estimated using these methods. The urban clusters with known populations were identified for

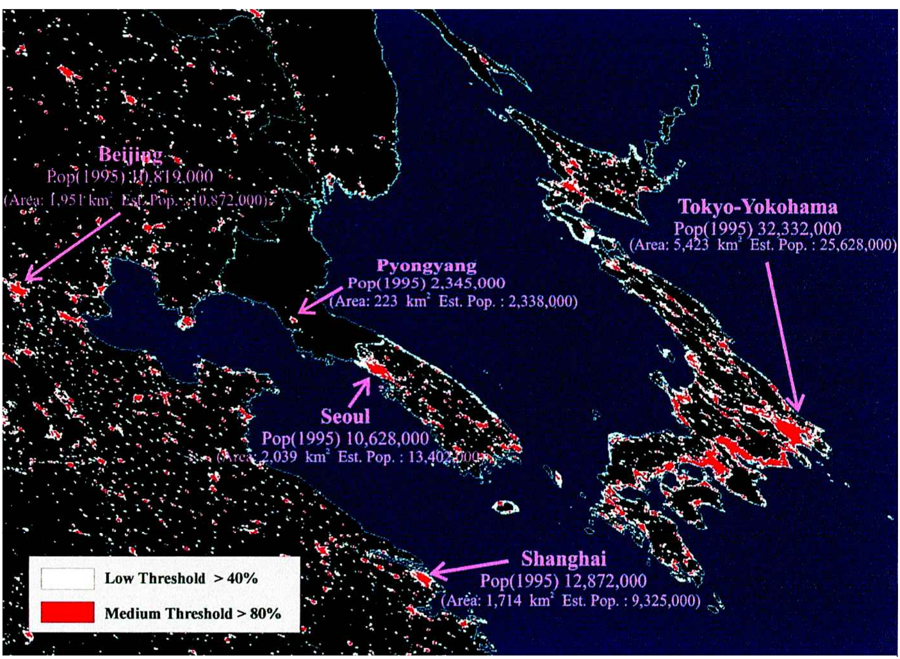

Figure 2. Two thresholds of the DMSP OLS imagery over Japan, Eastern China, and North and South Korea.

each nation of the world. A linear regression between the ln(area) and the ln(cluster population) was run on these points for each nation to identify a nationally specific slope and intercept parameter. The points in the regression were weighted with their known populations. The slope and intercept obtained were then used to estimate the population of every urban cluster the imagery identified in that country. The sum of the estimated populations of these urban clusters is the estimate of the urban population of the country. The total population of the country is calculated using published values for the percent of the nation's population that lives in villages and cities of over 2000 people (i.e. percent of population in urban areas) (Haub and Yanagishita 1997). An example of this population estimation method is provided for Venezuela (figure 3).

A large number of countries did not have a sufficient number of cities with known population to perform a regression analysis. In these cases, we used aggregate regression statistics. A regression analysis was run on the clusters of all the low-income countries, another regression on all the cities in medium-income countries, and another for the cities in high-income countries (based on their GDP/capita). If a country had no cities of known population the parameters from the appropriate aggregated regression were used (e.g. if the country had no identified clusters with known population and had a medium GDP/capita we used the regression parameters derived from all the cities with known populations that were in countries with a medium GDP/capita). Finally, if the country had only one city of known population, then the aggregate slope was used and the regression line was sent through the known city point, thus determining an intercept.

City Name	Cluster Area (km2)	Actual Population	Estimated Population	% Error
Caracas & Los Teques	1,054	3,489,000	2,138,416	-39
Maracay & Valencia	1,688	2,174,000	3,755,885	73
Maracaibo	869	1,618,000	1,697,628	5
Barquisimeto	514	885,000	905,913	2
Barcelona	326	477,000	525,513	10
San Cristobal	305	399,000	485,288	22
Merida	169	282,000	239,512	-15
Acariqua	161	218,000	226,016	4
Cabimas	357	204,000	585,822	187
Barinas	172	193,000	244,606	27
Coro	120	171,000	159,029	-7
San Fernardo de Apure	110	139,000	143,311	3
Guanare	111	131,000	144,871	11
Valera	146	120,000	201,067	68
Carupano	88	113,000	109,743	-3

No. Urban Areas w/ Known Population	15
No. Urban Areas identified w/ Imagery	205
Slope of Weighted Regression	1.196
Intercept of Weighted Regression	6.251
Theoretical Minimum Detectable Population	518
R2 of Ln(Area) Ln(Population) relationship	0.84
Estimated Urban & Toal Population of Venezuela	20,068,000 / 23,609,000
Actual Urban & Total Population of Venezuela	19,189,000 / 22,576,000

Figure 3. A graphic explanation of national population estimation for Venezuela.

3. Results

3.1. *Nationally aggregated estimates*

A linear relationship between ln(area) and ln(population) was established for each country of the world. The identified parameters and other relevant statistics are provided for the 60 most populous nations of the world (table 1). For 20 of the 60 most populous nations a single large city was used to estimate the intercept of the regression. (A table of the parameters, populations, errors and thresholds for *all* of the countries can be obtained from the first author.) The intercept of the regression for each country provides a theoretical minimum detectable population for a 1 km^2 urban area. For the same threshold of 80, these values were 1169 for high-income countries, 3548 for medium-income countries, and 7251 for low-income countries. (In the final analysis presented in table 1 we actually used a lower threshold of 40 for the lower income countries in order to capture more cities; this lower threshold produced a minimum detectable population of 1169 for the low-income countries.) Many wealthy countries such as Japan, Canada, and the USA had low minimum detectable populations as we expected (1 km^2 lit areas had predicted populations of 175, 157 and 128, respectively). High minimum detectable populations tended to occur for the less developed countries: North Korea, Ethiopia, Afghanistan and the Ivory Coast (1 km^2 lit areas had predicted populations of 20 171, 10 775, 15 245 and 10 604, respectively). However, not all nations fit these trends. For example, Uzbekistan, which has a relatively low GDP/capita, had the lowest minimum detectable population (57) of these 60 nations; while the Netherlands recorded the highest minimum detectable population with a value of 28 510. Some of these anomalies can be attributed to small sample sizes or the unusual population densities of single large or heavily conurbized cities in the nation in question; nonetheless, GDP/capita alone does not explain the variation. Nonetheless, this model's estimates of the national populations were within 25% of accepted values for more than 65% of the 60 most populous nations.

An independent estimate of China's population (1.512 billion) was made, which is 22% greater than the accepted estimate of 1.243 billion. The Chinese city population data were excluded from the parametrization process for two reasons: (1) the China data we obtained often confused city populations and populations of regional administrative boundaries, and (2) by excluding the Chinese cities we could estimate the urban and national population of China in an independent manner. There is an element of circularity in this method of estimating the population of urban clusters by using known populations. By removing the Chinese cities and applying the results of this study to them, the question of circularity is addressed, and the robustness of the method is tested.

3.2. *Interpreting variation in the 1n(area) vs 1n(population) relationship*

Explaining the variability of the regression parameters is difficult when looking at the hundreds of disaggregated national parameter estimates. Aggregation of the cities of the world to their national income class (e.g. low income: GDP/capita < \$1000/year; medium income: \$1000/year < GDP/capita < \$5000/year; and high income: \$5000/year < GDP/capita) allows for direct interpretation of the intercept parameter. A scatterplot of the ln(area) vs ln(cluster population) of these 1383 urban areas provides a sense of the strength of this relationship at five levels of

Table 1. National statistics, identified parameters and estimated populations for the 60 most populous countries of the world.

Country	% Population urban	GNP per capita	Income class	Slope	SE Slope	Intercept	SE* Intercept	R^2	Threshold	No. clusters with known population	No. clusters from DMSP	Total national population	DMSP est. of national population	Absolute error (1000s)	% Error	Minimum detectable population
China	30	3640	low	1.185	0.031	7.224	0.190	n/a	40	none used	944	1242500000	1512611819	270112	22	1372
India	26	340	low	1.339	0.028	6.317	0.178	0.93	40	179	1952	969729000	1026965385	57236	6	554
USA	75	26980	high	1.252	0.049	4.851	0.390	0.84	80	116	4215	267661000	285641333	17980	7	128
Indonesia	31	980	low	0.997	0.055	8.165	0.369	0.94	40	21	476	204323000	221735484	17412	9	3516
Brazil	76	3640	medium	1.186	0.048	7.446	0.317	0.87	80	85	944	160343000	190086842	29744	19	1713
Russia	73	2240	medium	1.202	0.051	6.986	0.300	0.84	80	105	796	147264000	140560274	−6704	−5	1081
Pakistan	28	460	low	1.302	0.113	5.955	0.743	0.90	40	18	396	137752000	100315307	−37437	−27	386
Japan	78	39640	high	1.389	0.069	5.166	0.548	0.81	80	62	487	126054000	135212821	9159	7	175
Bangladesh	16	240	low	1.369	0.053	6.180	0.336	0.99	40	10	100	122219000	91530000	−30689	−25	483
Nigeria	16	260	low	1.185	0.038	5.937	Ibadan	n/a	40	1	115	122000000	204711250	82711	68	8111
Mexico	71	3320	medium	1.508	0.042	4.653	0.303	0.97	80	55	635	95724000	95507606	−216	0	105
Germany	85	27510	high	0.858	0.080	8.120	0.523	0.76	40	39	602	82022000	57798542	−24223	−30	3361
Vietnam	20	240	low	0.926	0.161	9.111	0.980	0.89	40	6	66	75123000	89719000	14596	19	9054
Philippines	47	1050	medium	1.090	0.071	8.680	0.470	0.89	80	13	40	73419000	84700851	11282	15	10467
Iran	58	n/a	high	1.003	0.041	7.862	0.949	0.95	90	34	405	67540000	87544483	20004	30	2597
Egypt	44	790	low	1.617	0.457	5.131	2.970	0.86	90	4	108	64792000	82422273	17630	27	169
Turkey	63	2780	medium	0.917	0.052	9.198	0.307	0.91	80	37	245	63674000	88942857	25269	40	9877
Thailand	19	2740	medium	1.011	0.022	7.707	Bangkok	n/a	80	1	127	60088000	75687368	15599	26	2224
UK	90	18410	high	1.005	0.072	7.673	0.465	0.81	80	48	274	58800000	40789111	−18011	−31	2150
Ethiopia	15	100	low	1.185	0.038	7.518	Addis Ababa	n/a	40	1	28	58733000	34251200	−24482	−42	10775
France	74	24990	high	1.270	0.075	5.787	0.525	0.91	80	30	386	58633000	45240676	−13392	−23	326
Italy	67	19020	high	1.877	0.068	8.265	0.418	0.82	80	41	345	57429000	53629701	−3799	−7	3885
Ukraine	68	1630	medium	1.105	0.098	6.976	0.603	0.86	40	24	409	50719000	49354860	−1364	−3	1071
Zaire	29	120	low	1.185	0.038	6.292	Lubumbashi	n/a	40	1	27	47440000	28264862	−19175	−40	8587
Myanmar	25	n/a	low	1.185	0.038	7.654	Rangoon	n/a	40	1	55	46822000	47718000	896	2	9490
South Korea	74	9700	high	1.085	0.061	8.143	0.412	0.96	80	16	99	45850000	44867027	−983	−2	3439
South Africa	57	3160	medium	1.011	0.022	7.138	Johannesburg	0.89	80	9	254	42465000	31577393	−10888	−26	1259
Spain	64	13580	high	1.185	0.079	5.975	0.532	0.90	80	26	433	39330000	34920313	−4410	−11	393
Poland	62	2790	medium	0.912	0.049	7.650	0.304	0.93	40	26	352	38648000	35625771	−3022	−8	2101
Colombia	70	1910	medium	0.871	0.087	8.484	0.516	0.85	80	21	252	37418000	34367000	−3051	−8	4837
Argentina	87	8030	high	1.247	0.037	6.362	0.267	0.98	80	19	277	35558000	31491839	−4066	−11	579
Canada	77	19380	high	1.286	0.087	5.058	0.657	0.91	80	25	919	30142000	39815325	9673	32	157
Algeria	50	1600	medium	1.273	0.041	6.806	0.825	0.87	80	8	183	29830000	34106072	4276	14	903
Tanzania	21	120	low	0.867	0.131	9.025	0.706	0.91	40	6	31	29461000	27316429	−2145	−7	8308
Kenya	27	280	low	1.185	0.038	6.746	Nairobi	n/a	40	1	48	28803000	24234667	−4568	−16	6088
Morocco	51	1110	medium	1.230	0.176	7.276	0.980	0.86	80	10	99	28217000	28674118	457	2	1445
Sudan	27	n/a	low	1.185	0.038	5.788	Khartoum	n/a	40	1	59	27899000	34473293	6574	24	5693
Peru	70	2310	medium	1.298	0.068	6.715	0.439	0.97	80	14	83	24362000	20826857	−3535	−15	825
North Korea	61	n/a	low	1.185	0.038	8.357	Pyongyang	n/a	40	1	16	24317000	7921574	−16395	−67	20171
Uzbekistan	38	970	low	1.487	0.127	4.070	0.838	0.94	40	10	148	23672000	20264842	−3407	−14	59
Nepal	10	200	low	1.185	0.038	7.063	Kathmandu	n/a	40	1	22	22641000	27385300	4744	21	5162
Venezuela	85	3020	medium	1.196	0.143	6.251	0.950	0.84	80	15	205	22576000	23608824	1033	5	519
Romania	55	1480	medium	1.039	0.089	8.397	0.430	0.92	80	14	59	22535000	15525185	−7010	−31	4434
Afhanistan	18	500	low	1.185	0.038	4.605	0.230	0.51	40	0	13	22132000	22963667	832	4	15245
Taiwan	75	n/a	high	1.065	0.027	7.460	Tai-Pei	n/a	40	1	30	21535000	32999736	11465	53	1737
Iraq	70	n/a	low	1.041	0.041	7.346	0.651	n/a	40	1	147	21177000	21488916	312	1	1550
Malaysia	51	3890	medium	0.610	0.093	9.982	0.559	0.90	80	7	73	21018000	26904314	5886	28	21634
Uganda	11	240	low	1.185	0.038	7.252	Kampala	n/a	40	1	11	20605000	22130636	1526	7	7824
Saudi Arabia	80	7040	high	1.065	0.027	6.719	Jiddah-Mecca	n/a	80	1	280	19494000	32602000	13108	67	828
Australia	85	20090	high	1.186	0.179	5.989	1.295	0.84	80	10	248	18700000	19760941	1061	6	399
Sri Lanka	22	700	low	1.185	0.038	5.235	Colombo	n/a	40	1	37	18665000	12984318	−5681	−30	2827
Mozambique	28	80	low	0.985	0.317	8.871	1.693	0.90	40	3	21	18355000	20481929	2127	12	7122
Ghana	36	390	low	1.185	0.038	5.960	Accra	n/a	40	1	41	18102000	17891778	−210	−1	5437
Kazakhstan	56	1330	medium	0.814	0.186	8.802	0.995	0.76	80	9	80	16433000	16558929	126	1	6648
Netherlands	61	24000	high	0.612	0.045	10.258	0.274	0.97	80	8	48	15598000	16267148	669	4	28510
Yemen	25	260	low	1.185	0.038	6.620	Sanaa	n/a	40	1	66	15214000	14313992	−900	−6	2276
Ivory Coast	46	660	low	1.185	0.038	7.218	Abidjan	n/a	40	1	38	14986000	17579978	2594	17	10604
Syria	51	1120	medium	0.838	0.097	8.154	Damascus	n/a	80	1	53	14951000	7309078	−7642	−51	3477
Chile	85	4860	medium	1.011	0.022	8.585	Santiago	0.66	80	1	72	14800000	18849529	4050	27	5351

*Note: If SE of intercept column has a city name in it, that city was used to define the intercept.

aggregation: globally (all the points), for high income countries (green points), for medium income countries (blue points), for low income countries (red points), and for the known urban clusters of Venezuela (black points) (figures 1 and 3). At the aggregate level the estimates of the intercept parameter for the low, medium, and high-income countries are statistically significantly different. Figure 1 indicates that the intercept parameter is inversely related to GDP/capita. It is also interesting to note that the strength of the correlation of this regression generally increases when points are classified by national identity and analysed separately as they are done for Venezuela in figure 3.

3.3. *Aggregate estimates of total population and urban extent*

Estimates of the total populations of countries aggregated for: (1) all the low-income countries, (2) all the medium-income countries, (3) all the high-income countries, and (4) the whole planet are reported (table 2). Estimates of the urban populations of these nations using these parameters produces a global population estimate of 6.295 billion, which is 7% greater than the contemporaneous (1997) accepted estimate of 5.867 billion (table 2). The percent error between the aggregate estimates and known aggregate populations are less than 8%. Table 2 also summarizes DMSP OLS and USGS/IGBP (United States Geological Survey) based measures of urban landcover at these aggregate scales. The DMSP OLS uses lit area as a proxy measure of the areal extent of urban land cover for every nation of the world. An independent estimate of urban landcover (USGS/IGBP) was obtained (Loveland *et al.* 1991, Belward 1996) and compared to the DMSP OLS derived estimate. In virtually all cases the urban extent as measured by the night-time satellite imagery exceeds those of the USGS/IGBP global landcover dataset. The DMSP OLS based measure estimates 0.81% of the Earth's land to be urbanized, a number that is 4.5 times larger than the IGBP figure of 0.18%. The night-time imagery has a bias towards overestimation of urban extent because a small well lit area will fill a 1 km^2 pixel; nonetheless the DMSP OLS derived night-time imagery is being considered by the USGS as an improved means of delineating urban extent for its global landcover maps (Loveland 1997).

Table 2. Aggregate estimates of population and extent of urban land cover.

Population estimation No. of clusters with known population	Slope	SE Slope	Intercept	SE Intercept	R^2	Actual population	Estimated population	% Error
Total world (1 threshold = 80; n=1404)	0.85	0.016	9.017	0.102	0.68	5 867 566 272	6 224 626 469	6.1
Total world (multiple thresholds; n=1393)	n/a	n/a	n/a	n/a	n/a	5 867 566 272	6 293 454 419	7.3
High income (n=471)	1.065	0.027	7064	0.201	0.77	1 074 842 200	1 105 827 550	2.9
Medium income (n=575)	1.011	0.022	8174	0.141	0.78	1 127 715 000	1 166 132 502	3.4
Low income (n=347)*	1.189	0.031	7425	0.19	0.81	3 665 009 072	3 952 666 417	7.8

Urbanization estimation	Total area (km^2)	Urban area by DMSP	Urban area by IGBP	% Urban cover by DMSP	% Urban cover by IGBP
Total world	143 393 924	1 158 977	257 085	0.81	0.18
High income†	40 314 690	646 722	132 710	1.60	0.33
Medium income	47 557 079	298 300	89 641	0.63	0.19
Low income	55 522 155	258 012	34 734	0.46	0.06

* Threshold = 40.
† Low income: GDP/capita <$1000/year;
medium income: $1000/year <GDP/capita <$5000/year;
and high income: $5000/year <GDP/capita.

3.4. *Results for selected large urban agglomerations*

Actual and estimated populations with percent errors are reported for the urban clusters of the world with known populations in excess of 10 million and for the Chinese urban clusters with estimated populations in excess of 10 million (table 3). The conurbation or 'melding together' of nearby cities warrants some discussion at this point. The New York cluster of the USA extended to include cities in Connecticut, Long Island, New Jersey and Pennsylvania. This cluster was split in half by the Hudson River. This 'breaking up' of large clusters results in underestimates due to the exponential relationship between areal extent and population of urban clusters. In some cases the opposite problem (e.g. a substantial overestimation) can occur when several smaller clusters meld into a 'super-cluster'. We believe this occurred in the Guangzhou–Dongguan–Shilong–Foshan cluster in China that borders and conurbizes with Hong Kong. This urban cluster had the highest estimated population (28.3 million) of all the urban clusters of the world. These large conurbations present some problems with respect to population estimation. When the linear regressions at the national level were performed, many points with large outliers were examined directly in the GIS database; most of these outliers exhibited problems associated with conurbation. Conurbation corrections were made for some of these cities including Istanbul, Stockholm and Hong Kong–Guangzhou.

4. Discussion

At the aggregate level (i.e. the whole world) a correlation is observed between the areal extent of an urban cluster (as identified by night-time satellite imagery) and its corresponding population. Disaggregation of this information to three nationally aggregated income levels greatly increases the strength of this correlation. General trends across income levels are observed with respect to both the slope and intercept of this relationship. However, the effect of the intercept is more pronounced and suggests that a small city of a given area in a low-income country will have a higher population (and population density) than a city of the same areal extent in a wealthy country. The cause of this is likely to be the availability of modern transportation: cities in which cars, buses, and rail are not as available will be more compact and have higher population densities. A time-series study of the same ln(area) vs ln(population) of the city of Ann Arbor, Michigan shows a dramatic change in the relationship

Table 3. Urban clusters with populations of 10 million or more.

Name of cluster	Area of cluster (km^2)	Actual population of cluster	Estimated population of cluster	% Error
Tokyo–Yokohama	5423	32332000	27049627	–16
New York–Philadelphia*	4930 & 7990	25608700	15274060	–40
Mexico City	3065	18459901	18923719	3
Bombay	1579	16748782	10650617	–36
Sao Paulo	2036	15980500	11493200	–28
Los Angeles	8534	15047800	10669187	–29
Manila–Quezon City	1269	14519828	14205262	–2
Calcutta	1541	13880513	10308818	–26
Seoul	2039	12892776	13362102	4
New Delhi	2245	12819200	17061602	33
Buenos Aires	2969	12294276	12372510	1
Chinese cities with estimates greater than 10 million				
Beijing	1951	10819000	10871719	0
Guangzhou (multi-city conurbation)	4371	?	28276887	?

*The New York–Philadelphia cluster was many city conurbations split into two pieces by the Hudson River which contributed to the underestimation.

after World War II; this corresponded with the widespread use of the automobile in that city (Tobler 1975).

The variation of the slope of this relationship across the three income levels actually counteracts the effect of the intercept and has its greatest influence in the largest cities. The trend to higher population densities for progressively larger cities is more pronounced in the wealthier nations as indicated by the higher slopes for the wealthier nations (figure 1). The explanation for this could be the combined effects of high demand for central business district property in the large cities of the wealthy nations, and, the ability of these nations to provide the infrastructure to support and build very high density housing (skyscrapers, etc.). In any case, variation in the intercept parameter was much more significant than variation in the slope between nations and income classes. This agrees with earlier findings of Stewart and Warntz (1958) in a similar analysis of cities and villages in Europe.

Aggregation averages the errors in the over and underestimates of both the cluster and national population estimates; this is similar to how signal averaging eliminates noise. However, if aggregation were simply analogous to signal averaging then the scatterplot of the ln(area) vs ln(population) for the cities of known population in a particular country would not be expected to have any stronger a correlation than a random selection of cities from around the world. Nonetheless, this is not what was observed. The increased strength of the ln(population) vs ln(area) relationship via aggregation by GDP per capita has been demonstrated. The scatterplot of the urban clusters of Venezuela (figures 1 and 3) show how national aggregation typically increases the strength of this relationship. The fact that a much stronger relationship exists for the urban clusters of any given nation suggests that future research on the influence of the spatial attributes of the data in question can prove to be quite useful in improving the explanation of the relationship between the areal extent and population of an urban area.

4.1. *Discussion of error*

Explicitly defining the error in this study is difficult if not impossible. There is no ‘official’ estimate of the world’s population and our knowledge of the world’s total human population has at most two significant figures and most likely only one (i.e. we know the billions place). The United Nations recently declared that the 6 billionth human being was born on 12 October 1999. However, the USA Census claimed that we reached the 6 billion milestone in June of 1999. Estimates of the population of the cities and countries of the world are just that: *estimates*. The errors we have described in the paper are comparisons between our estimates and existing estimates. Existing estimates of city and national populations vary dramatically in quality and availability. Some of the ‘error’ in our estimates of city populations are due to real variation in the ln(area) vs ln(population) relationship; however, some of the error is in the erroneous values we have for the ‘known’ population of urban clusters. In addition, errors in the percent of population living in urban area figure we used to estimate national populations will introduce error into those estimates. Future research in this area will require an accurate population figure for a large number of cities throughout the world.

We have parametrized a simple model based on a potentially crude set of city population values. In this effort we used the best globally available population data for the cities of the world. In a previous investigation of the ‘city lights’ data for the USA (Sutton *et al.* 1997), we compared the DMSP OLS imagery to a higher quality, higher spatial resolution, full population density grid of the USA produced by the Consortium for International Earth Science Information Network (CIESIN) (Meij 1995). In that study using the CIESIN data we obtained an area and a population figure for over 5000 points (every urban cluster identified by the night-time imagery). The regression analysis using all 5000 urban clusters had no problems with statistical boundaries (population in metro area vs population within city limits); nor did it have the kinds of conurbation problems we ran into with point data; and it was of higher quality and accuracy than the point data used in this study. This study found that the DMSP OLS imagery captured 79% of the US population in the lit areas. This is only 4% greater than the 75% of the US population that lived in urban areas.

In this global study we only had 116 urban clusters with known population and area for the USA. The regression results were substantially improved by using higher quality data and avoiding these problems: $R^2 = 0.98$ with the CIESIN data vs $R^2 = 0.84$ with the point data. This improvement suggests that the relationship described here is in fact stronger than the results of this global investigation suggest. The errors in the 'known' city populations of this study accounted for much more of the error than real variation in the ln(area) vs ln(population) relationship in the USA. The circularity introduced by using known populations of cities will introduce bias in our results if there is any bias in the city population estimates. We believe that many city population estimates are underestimates for several reasons. First, many city population figures represent the population within the legal boundary of the city rather than the metropolitan area population. Secondly, large conurbations of several cities often include many small cities (typically less than 100 000) that were not on our list of cities with known population, thus biasing the estimates of many of the conurbation clusters towards the low end. Finally, virtually every city for which extra information was sought had a population substantially higher than the published figures.

For example, conventional wisdom in Mexico (and among many population experts) suggests that the population of Mexico City in 1997 was somewhere between 21 and 24 million. The official figure we used was 18.5 million. This has a substantial influence on the estimate of the national population of Mexico. The estimate of Mexico's population would have been significantly higher had we used a larger estimate for the population of Mexico City. The case for Riyadh, Saudi Arabia was so dramatic that we did not use the published population of Riyadh and simply drew a line with a pooled slope parameter through the conurbation of Jiddah and Mecca to define the intercept for Saudi Arabia. The Jiddah–Mecca conurbation and Riyadh had areal extents of 2213 km^2 and 2317 km^2, respectively. Yet our population numbers for these two clusters were 3.2 and 1.3 million, respectively. The resulting estimate of Riyadh's population was 3.2 million, which agreed closely with expert opinion on the population of Riyadh (3.3 million) (Al-Sahhaf 1998).

Because we believe there is a bias toward underestimation of the 'known' city populations, we believe that it is very unlikely that our aggregate estimates are overestimates. If the numbers we used for the percent of population in urban areas on a national basis are accurate, it is very likely that our global population estimate of 6.3 billion is reasonable or perhaps even an *under*estimate. In any case, it is a sobering thought to contemplate the implications of 400 million more people on the planet. Our number is sufficiently different from the accepted 5.9 billion to have significant impact on commonly calculated numbers such as global grain production per capita, per capita availability of freshwater, and per capita consumption of seafood.

Defining the errors in the model is difficult because the model is sensitive to both the data it is parametrized with (the known city populations), and the percent of population in urban areas figures it uses on a national basis. However, in an ongoing study with the 'low-gain' data we have compared our models of population density within the USA and derived from the DMSP OLS imagery to a state-of-the-art global population dataset known as the global demography project. The global demography project was a joint effort of Environmental Systems Research Institute (ESRI), CIESIN and the National Center for Geographic Information and Analysis (Tobler *et al.* 1995, Tobler *et al.* 1997). Our model of population density had better correlations to the population density grid derived from the 1990 US census than the global demography project data. DMSP OLS based models outperformed the global demography project at 1, 5 and 10.4 km square scales (e.g. pixel edge length). Despite the errors in this model it compares well to state-of-the-art representations of the global human population. Combining models utilizing the non-biased nature of the global demography project with the fine spatial resolution information in the DMSP OLS imagery could provide global representations of human population and population density of unprecedented quality.

4.2. *Future research to improve the model*

We hope to explore several means of improving the accuracy of this model's population predictions. We also hope to develop the theory that explains the spatial variation of the area–population relationship. The use of three thresholds as a proxy measure of the areal extent of the urban clusters is limited and we hope to improve upon this substantially using the low-gain data product. Incorporation of daytime global imagery derived from other regions of the spectrum could improve the accuracy of the measure of an urban cluster's areal extent. Synthetic Aperture Radar, AVHRR's NDVI 'greenness' index and Landsat Thematic Mapper (TM) imagery all show promise for improving the delineation of the urban extent (Harris 1985, Khorram *et al.* 1987, Haack and Slonecker 1994, Henderson and Zong-Guo 1998). In addition we anticipate the low-gain, radiance calibrated, night-time light intensity global imagery to be a substantial improvement on the percent observation based data product used in this study (Elvidge *et al.* 1998). The low-gain product captures large areas of low intensity diffuse radiation not captured in the stable lights dataset; consequently such a dataset shows promise for modelling population density in many rural areas. Also, because the low-gain data are a measure of actual light intensity, they may prove useful as a proxy for energy consumption and be used to differentiate population estimates of equal area clusters within a country.

4.3. *A Census from Heaven?*

Historically many efforts have been made to estimate population and delineate urban extent via the use of daytime aerial photography and satellite observations (Clayton and Estes 1980, Forster 1985, El Sadig Ali 1993). These efforts have been limited in their success, and have proven difficult if not impossible to perform at a global scale. Night-time satellite imagery provides a profound focus on those areas of the earth where human activity dominates the landscape.

A 'Census from Heaven' (Stern 1985) via satellite imagery is no substitute for an actual enumeration of the population. In fact, the methods described here would be impossible without the ground data provided by earlier censuses of cities. However, as the population of the less developed countries grows, and as the income gap between the rich and the poor countries of the world also grows, the quality and availability of census data for a growing proportion of the world's population will continue to deteriorate. For example, the most recent census of Guatemala, executed in 1994, was doubtless the most thorough ever undertaken in that country, and included hundreds of populated places never previously enumerated. Nevertheless, the spatial characteristics of these data are rudimentary, especially in the country's northern and eastern lowlands (notably in the departments of Peten, Alta Verapaz and Izabal), which have undergone rapid colonization—and concomitant deforestation—during the past quarter century. The 'maps' supplied to enumerators in these frontier districts were generally hand drawn and based on anecdotal information, and as such were often grossly inaccurate. As a consequence, while we have better information than ever before regarding the size and character of the Guatemalan population, particularly on the frontier, we still lack a clear sense of where these people are. Models derived from DMSP OLS imagery may provide some of the best population distribution information available for many parts of the world in the decades to come.

Ideally the methods described here will serve as a base map to supplement a thorough census of the world's population that included age and sex structure, fertility rates, and other useful information. The methods described here are sufficiently simple to perform globally on an annual basis for a fraction of the cost of most national censuses. The DMSP satellites have been in orbit since the early 1970s and archives exist from which historical measures of urban extent could be produced. Inclusion of night-time satellite imagery into the suite of tools used for national censuses could improve the mapping and accessibility of global census data. The raster nature of this model's output lends itself to inclusion in many environmental models related to global change.

5. Conclusion

Historically, accurate knowledge of the size, behaviour and spatial distribution of the human population has been useful for understanding many social and political processes and phenomena. This knowledge will be necessary for comprehending, preventing, mitigating and/or adapting to many economic and environmental consequences of global change. Without accurate knowledge of the location, activity and number of people on the planet the human dimensions of global change cannot be understood. Most natural resources, including biological diversity, freshwater stores and cropland, vary dramatically in their availability across the surface of the earth. The major threat to these resources is human activity, which also varies dramatically across the surface of the earth. Models derived from night-time satellite imagery have the potential to dramatically improve our knowledge of the spatial distribution and intensity of human presence on the surface of the planet. In addition, the data products derived from night-time satellite imagery provide a novel empirical definition and measurement of 'urban' as a land cover classification. This information can only improve our ability to respond appropriately to many of the population-related challenges we currently face.

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