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Estimation of Gross Domestic Product at Sub-National Scales using Nighttime Satellite Imagery

Paul C. Sutton[1], **Christopher D. Elvidge**[2] and **Tilottama Ghosh**[3]

[1]Department of Geography
University of Denver, Denver, CO 80465, USA
Email: psutton@du.edu

[2]Earth Observation Group
NOAA National Geophysical Data Center
325 Broadway, Boulder, Colorado 80303, USA
Email: chris.elvidge@noaa.gov

[3]Department of Geography
University of Denver, Denver, CO 80208, USA
Email: tghosh@du.edu

Abstract

There is a degree of uncertainty in the measurement and/or validation of national and sub-national economic data such as Gross Domestic Product (GDP). In some circumstances it can be very useful to have alternative measures of numbers like GDP to provide evidence for the validation or invalidation of claims of some nations or regions regarding their economic productivity. This research explores the feasibility of developing predictive relationships between observed changes in nighttime satellite images derived from the Defense Meteorological Satellite Program's Operational Line scan System (DMSP-OLS), and changes in population and Gross Domestic Product (GDP).

Key Words*: nighttime satellite imagery, GDP estimation, informal economy, GIS, remote sensing*

Mathematics Subject Classification: 62J05.

Journal of Economic Literature (JEL) Classification: O17.

INTRODUCTION

The societal, commercial, and private *value* of satellite imagery (and other remotely sensed data) has been increasing at different rates for different applications. In the early days of remote sensing it was often argued that the benefits of satellite imagery, aerial photographs, and the geographic information systems that linked them all together were oversold to some extent. However, few people, if any, would question the value of hurricane warnings derived from satellite images. The myriad possibilities of the range of applications are too numerous to list in this paper; however, the potential benefits (and perhaps costs) of remotely sensed imagery and data are profound and growing rapidly. Just as the benefits of computers seemed to lag the hype associated with them, the benefits (or at least possibilities) associated with remotely sensed imagery and data are becoming increasingly profound. The 'Google Earth' application alone has significant implications, and perhaps both positive and negative consequences, for society at local, regional, national, and global levels (http://earth.google.com/).

We find it exhilarating to type in our own address into Google Earth and zoom into a relatively high resolution image of our own home. However; it might not be so exhilarating to click on the image of one's own home and find photographs of you and your family members and their associated credit card numbers, social security numbers, health records, amazon.com purchases, and other presumably private/personal information. In fact, we and our students take some solace in the fact that we can identify errors in Google Earth's database; however, it does seem to be only a matter of time until the data underlying applications such as Google Earth will only get better and better. These "improvements" will probably be in the domain of the spatial and temporal resolution of the imagery but are clearly linkable to countless other kinds of information that many of us might prefer not to be linked to this 'view of the world'. This kind of technology used in conjunction with GPS enabled tracking devices has elicited warnings regarding the coming age of 'geoslavery' (Dobson and Fisher, 2003). From this perspective we cautiously present one of many methods that have been, and will be, proposed for improving the availability and accuracy of spatially referenced information that can be estimated and/or inferred about people on the surface of the planet.

While satellite imagery is commonly used to measure physical attributes of the earth's surface typically associated with weather, land cover, temperature, topography, etc. it is increasingly being used to estimate and in some cases measure many characteristics of the surface of the earth that are associated with human impacts and or activity (de Sherbinin et al., 2002). Among these applications are: 1) Measuring urban extent and human impact on Net Primary Productivity and soil resources (Imhoff et al., 1997; Small, 2001; Milesi et al., 2003) , 2) Measuring Anthropogenic CO_2 emissions (Doll et al., 2000), 3) Measuring Anthropogenic Impervious Surface Area (Elvidge et al., 2004), 4) Estimating Urban Populations (Sutton et al., 2001), 5) Estimating intra-urban population density (Sutton, 1997; Sutton et al., 2003), 5) Mapping nocturnal squid fishing (Rodhouse et al., 2001), 6) Mapping 'exurban' areas (Sutton et al., 2006), 7) Mapping fire and fire-prone areas (Cova et al., 2004), 8) Mapping marketed and non-marketed economic activity (Sutton and Costanza, 2002), 9) Characterizing impacts of anthropogenic nocturnal emissions on sea turtle breeding behavior (Salmon, 2005), and 10) Mapping and estimating the Gross Domestic Product of nations at national and sub-national levels (Sutton and Costanza, 2002; Ebener et al., 2005). Most of the applications listed use little or no point source survey information. Some of the aforementioned studies take advantage of spatially referenced survey information such as U.S. census data that takes great pains to insure the privacy of its survey respondents. Nonetheless, "*the game is afoot*" (Doyle, 1992), and spatially referenced primary survey data will inevitably and increasingly be used to inform satellite imagery to estimate and/or infer the reality and impacts of spatio-demographic variation of and on the surface of the earth.

The research we present here builds on earlier work by Ebener and colleagues associated with using nighttime satellite imagery for modeling the distribution of income per capita at sub-national levels (Ebener et al., 2005). Ebener's paper explored the use of nighttime imagery for mapping GDP with health implications in mind. Aggregate national poverty data often masks sub-national variation which hinders the planning and delivery of health care to areas that need it. It has long been recognized that there are positive correlations between health and income (Benzeval and Judge, 2001). Development of alternative means of mapping wealth and poverty is deemed valuable because the reliable measurement of income in poor countries is often inaccurate; and, coarse in spatial and temporal resolution (Ahmad, 1994). In addition, there are many reasons to believe that individual household survey information regarding income are under-reported (Visaria, 1980; Deaton, 1987; Anand and Harris, 1994). This paper explores different methodologies for obtaining independent estimates of GDP at finer spatial resolution than is normally available.

METHODS

The datasets used in this study were the global population database known as Landscan (Dobson et al., 2000), a 1992-93 and 2000 DMSP OLS city lights composite (Elvidge et al., 2001) and sub-national GDP figures for the nations of India, China, Turkey, and the United States. The nighttime image data products used in this study do suffer from saturation of the digital number (DN) values in the cores of urban centers. This presents some problems with respect to simple integration or summing of lights as a proxy measure of light emission from a given area. Consequently, two approaches were used incorporating DMSP OLS nighttime imagery as a proxy measure of economic activity. The first used an integration (aka summing of light intensity values) and suffered the consequences of saturation; whereas, the second method used the areal extent of lit areas and a non-linear relationship between population and areal extent to create a proxy measure of GDP. In addition, a regional parameter was derived from errors in the 1992-93 data and applied to the 2000 data.

The development of the models proceeded as follows. Simple log-linear relationships between the sum of lights observed by the DMSP OLS and the GDP of nations are used as a starting point (Sutton and Costanza, 2002; Ebener et al., 2005) (Figure 1). We disaggregated the DMSP OLS observations to the first sub-national administration level (states and cantons) for India, China, Turkey, and the United States. These state level light integrations were regressed using simple linear regression on the corresponding state level GDP values and the residuals from these regressions were stored and sorted based on the magnitude of their residuals. We then created a “region” parameter by dividing the states into five quintiles (1-5) based on their error. This “region” parameter was then used as a nominal variable via dummy coding to predict the 1993 GDP of each state. The regression parameters thus derived were applied to the 2000 GDP of each state. Tables 1-A and 1-B provide an example of this process for the nation of China. Tables like this were developed for China, India, Turkey, and the United States. Scatter plots and maps of the model development for these four nations are provided in Figures 2-A and 2-B.

Table 1-A: Regional Parameters for Chinese Cantons

Canton	Population	DMSPSUM9293	GDP1993	OLSerr1993	Region
Shanxi	31868720	443302	62263	-103363	1
Heilongjiang	39022690	482679	106310	-71986	1
Xinjiang	16794560	289470	44674	-71455	1
Nei Mongol	23776920	272057	47067	-63459	1
Hebei	67687330	533609	149393	-45290	1
Jilin	27325100	236024	63434	-35498	2
Ningxia	5158847	60099	9172	-33154	2
Gansu	24790140	127170	32889	-31019	2
Shaanxi	36437990	205104	59318	-29665	2
Qinghai	4938862	43999	9685	-27461	2
Xizang	2433427	8977	3293	-22584	2
Tianjin	9735383	144513	47366	-22121	3
Hainan	7266549	46563	22802	-15169	3
Guizhou	35893540	88743	36761	-14782	3
Beijing	11989330	176111	76297	-3357	3
Yunnan	40970460	151627	68846	-2930	3
Guangxi	46813840	143282	78951	9860	3
Henan	94755800	353889	146912	10056	4
Liaoning	43726540	446788	177665	10918	4
Jiangxi	41787940	84553	63885	13690	4
Fujian	33297370	147822	100149	29596	4
Guangdong	69623060	689394	284970	40162	4
Shandong	93518330	561627	245580	41883	4
Hubei	59804980	168832	125850	48538	5
Hunan	67218970	122092	112941	50668	5
Shanghai	14784580	132493	133557	67937	5
Zhejiang	45927530	229134	168712	71997	5
Sichuan	118811800	208260	185228	95229	5
Jiangsu	74307460	432467	264901	102762	5

Title of the columns in Tables 1-A	Description of the columns in Tables 1-A
Canton	the name of sub-national administrative areas of China
Population	the corresponding population of the Canton
DMSPSUM9293	the integration or sum of all the year 1993 pixel values that are in the corresponding canton
GDP1993	the GDP of that Canton in 1993
OLSerr1993	the error or residual resulting from a simple linear regression of DMSPSUM9293 on GDP1993
Region	the quintile ordinal classification of each canton based on the magnitude of their residual from the simple regression

Table 1-B: Actual and Estimated GDP of Chinese Cantons

DMSPSUM2000	GDP2000	PredGDP2000	ErrGDP2000	PcErr2000
566921	94594	141629	47035	50
647196	187196	171078	-16118	-9
521463	78513	124952	46439	59
422853	80622	88776	8154	10
831553	292848	238711	-54136	-18
367749	104802	122883	18081	17
83245	15282	18510	3228	21
198291	56588	60716	4128	7
367604	95579	122830	27251	29
64946	15168	11797	-3371	-22
21987	6759	-3963	-10722	-159
191185	94338	79401	-14938	-16
89342	29836	42039	12202	41
164921	57173	69765	12592	22
240100	142642	97345	-45297	-32
357806	112507	140527	28020	25
236636	117977	96075	-21902	-19
533266	295650	225839	-69812	-24
629777	268684	261244	-7440	-3
130583	115268	78111	-37157	-32
332421	225583	152157	-73426	-33
1162340	556020	456620	-99400	-18
949784	491581	378642	-112939	-23
310349	246084	199978	-46106	-19
227557	212452	169605	-42847	-20
189555	261899	155664	-106235	-41
504602	347365	271241	-76124	-22
429855	322232	243820	-78413	-24
664972	493899	330074	-163825	-33

Title of the columns in Tables 1-B	Description of the columns in Tables 1-B
DMSPSUM2000	the integration or sum of all the year 2000 pixel values that are in the corresponding canton
GDP2000	the GDP of that Canton in 2000
PredGDP2000	the predicted value of the GDP of each Canton derived from using the regression parameters from 1993 on the DMSPSUM2000 values
ErrGDP2000	the absolute error from the regression
PcErr2000	the percentage error from the regression

The second approach to model development used relationships recognized by Tobler and by Stewart and Warntz and applied by Sutton (Stewart and Warntz, 1958; Tobler, 1969; Sutton et al., 1997) (Figure 3). This approach attempts to avoid the problems of saturation in the DMSP OLS imagery by measuring the areal extent of lit areas in the nighttime satellite imagery rather than measuring intensity on a pixel by pixel basis.

Using a log-log relationship between the areal extent of urban areas and population we obtain an approximation of the ‘urban population’ of every state of which the sum is used as a measure of total urban population. This measure of urban population is used as a proxy measure of GDP in that state. The DMSP OLS imagery is thresholded at a uniform DN value of 30 to identify urban extent. These ‘blobs’ of light are overlaid over the Landscan Population density data to create a table of ‘urban blob area’ and ‘corresponding population of urban blob’. A log-log regression is applied to these data to produce an estimate of ‘urban population’ of each sub-national administrative unit. Because these measurements are measured relative to one another *within* a nation the varying levels of GDP per capita *between* these nations do not present a problem. The results of these regressions demonstrate the strong nature of this relationship (Figure 4).

The rationale for this approach is that despite the varying levels of economic development around the world, urban populations make the greatest contribution to

measured economic activity. We believe this is an improved measurement despite the dramatically varying levels of GDP per capita across these nations and throughout the world. These estimates of ‘urban population’ are used as predictor variables of GDP for the sub-national administrative units. Tables similar to those produced in Table 1 were prepared for this approach. Similar regression models using the same ‘region’ parameters were developed that characterized relationships between ‘urban population’ and GDP.

The methods developed here build upon previous attempts at estimation of GDP by contrasting the simple light-summing approach with the log-log areal extent (estimation of urban population) approach (Ebener et al., 2005). In the results section that follows we will show how this approach was a significant improvement in all cases; however, the magnitude of improvement varied dramatically.

RESULTS

The regression models developed for estimating GDP at the state level for the four nations can be obtained with all the GIS data layers and tables at the following URL (www.du.edu/sutton/GDPestimationData). The urban population estimation approach had a higher R^2 for every country we applied the models to (Table 2). However, the improvement was most dramatic for the nation of Turkey. This is undoubtedly due to the fact that Istanbul is a primate city that accounts for a larger fraction of the GDP of its nation than the largest cities in any of the other countries we chose to study.

Table 2: Regression models for estimation of GDP using the light summing and urban population estimation model for China, India, Turkey and United States.

	China	India	Turkey	United States
Simple Model R^2	0.94	0.70	0.58	0.70
Urban Model R^2	0.96	0.84	0.95	0.72

Consequently, the state that included the city of Istanbul was an outlier from the rest of the data which improved the R^2 for Turkey. Scatter plots of the predicted GDP vs. Actual GDP which include maps of the percent error of estimate for the states of the nations described in Table 2 can be found in Figure 5 (simple light summing) and Figure 6 (urban population estimation).

Inspection of these figures shows that the distributions of percent error for these models are not normal. Typically the errors of estimate of GDP for these states were greatest in percentage terms for the states with very small GDPs and small populations. Consequently the mean absolute deviation (MAD) of the percent error of these models was rather high (Table 3) and did not vary systematically from one model to the other (e.g. the light summing model performed better for two of the nations as did the urban population estimation model).

Table 3: Mean absolute deviation of the percent errors of the light summing and urban population estimation model.

Nation	Number of States	MAD (%)	MAD (%)
		(Light Summing)	(Urban Pop Estimation)
China	29	87	104
India	32	111	96
Turkey	67	43	32
United States	49	87	97

However, in the aggregate (e.g. by summing the GDP estimates of all the states) the urban population estimation model outperformed the light summing model in every case and had an aggregate percent error of *zero* for three of the nations (China, United States, and India) (Table 4).

Table 4: Estimated GDP values of 2000 using the light summing model and the urban population estimation model.

Nation	Actual GDP (2000)	Estimated GDP (2000) (Light Summing)	% Error (overall)	Esimated GDP (2000) (Urban Pop Estimation)	% Error (overall)
China	5,419,142	4,546,065	-16	5,419,143	0
India	1,006	1,357	35	1,005	0
Turkey	81,417,116	233,426,582	187	165,252,166	103
United States	9,199.44	9,163,464	0	9,199,392	0

These results suggest that spatial disaggregation of estimates dramatically improves aggregate national estimates by including the population information provided by the Landscan dataset and using the urban population estimation methodology. This is likely to be of interest to geographers because it provides quantitative evidence for the spatial perspective in solving an interesting and perhaps important problem.

DISCUSSION

Nighttime satellite imagery is profound in the focus it obtains on human activity and presence. Nonetheless, the coarse spatial and spectral resolution of the DMSP OLS derived data products presently lend only crude (yet statistically significant) abilities to estimate aggregate urban populations, intra-urban population densities, and in this case, sub-national GDP figures. The Mean Absolute Deviation of percent error of state level GDP estimates shown here are quite large; however, it should be noted that the large errors are almost universally the estimates of those states with very low GDPs. It remains an interesting question to ask as to what finer spatial, spectral, and temporal resolution nighttime imagery might be capable of informing us of. In any case, the aggregation of these state level estimates to national level GDP estimates are strikingly accurate (0% error for three of the four countries in this case). These results are encouraging enough to suggest that it may be possible to map economic activity at sub-national levels even with these relatively crude methods. These methods, despite their crude levels of accuracy, may be useful for making estimates of the magnitude of the informal economy in many parts of the world.

An interesting question to ask in light of the foreseeable and inevitable improvements to the spatial and temporal resolution of applications such as Google Earth is: *Will nighttime satellite imagery still have any useful applications once we can pan, zoom, tilt, spin, and fly anywhere on the earth with high resolution DAYTIME imagery?* We believe the answer is "yes". The particular application we have investigated here constitutes what we are convinced is a poignant example. Nighttime imagery has a great deal of information to provide with respect to economic development and associated energy and transportation infrastructures. We have conducted this study as "arm-chair" analysts with little or no expert knowledge of most of the regions we analyzed yet it presents opportunities for making estimates of economic variables such as gross domestic product despite our ignorance. No daytime satellite image of the surface of the earth could provide such a profound measure of wealth and the important socio-economic variables associated with wealth.

In the past few years many people have begun to conduct research on the potential of remotely sensed imagery for mapping and making inferences regarding phenomena that are primarily in the domain of the social sciences (Liverman et al., 1998; Rashed and Weeks, 2000; de Sherbinin et al., 2002; Rashed and Weeks, 2003). The mapping and estimation of fertility, income, travel behavior, and access to clean water, public transportation, education, contraception, and health services are important questions to social scientists and policy makers. Historically, conducting the surveys needed to answer these questions and make assessments have been labor intensive and expensive. Identifying methods in which satellite imagery can reduce the costs and enable this kind of information acquisition is a growing area of research. Increasingly primary data acquisitions such as health and fertility surveys are being gathered with spatial reference enabled by cheap and relatively accurate GPS devices. This kind of information, utilized in tandem with remotely sensed imagery, will present myriad opportunities for improving and expanding our ability to map not only the spatial distribution of the human population but the conditions in which they live and their economic, spatial, and demographic behaviors. The ethical, moral, and legal implications of these possibilities are profound; and indeed, '*the game is afoot*'.

CONCLUSION

This paper presents a contrast of two methods for estimating GDP at sub-national levels for the nations of China, India, Turkey, and the United States in the year 2000. One method essentially reproduces ideas presented by Ebener and colleagues, which simply sum light intensity DN values in nighttime satellite imagery (Ebener et al., 2005); whereas, the second method applies a spatial analytic approach to the patterns in the nighttime imagery as they relate to population density. The second method was somewhat superior to the first; nonetheless, neither method is presently superior to sophisticated measures of GDP that are presently conducted in the developed world. Despite this fact, we believe these methods could make useful measures of the magnitude and spatial distribution of both the formal and informal economy in parts of the world where measures of economic activity are not very sophisticated. In a more general sense these methods represent one of many manifestations of the beginning of the use of remotely sensed imagery for mapping and inferring phenomena that have historically landed in the domain of the social sciences. Continued development of methods such as these will likely raise many moral, ethical, political, and legal questions that remain to be resolved. The inadequate governmental response to Hurricane Katrina suggests that the potential benefits of spatio-demographic information are not presently being utilized to their full extent. The potentially negative consequences associated with large corporate and governmental institutions having access to high quality spatio-demographic information may not ever be seen by the public. Consequently, we believe a great deal of thought should be given to the ethical, moral, political, and legal consequences associated with the information that is potentially obtainable via the merging of remotely sensed imagery and myriad other sorts of databases. We take some solace in the fact that the methods presented here are not that accurate; however, we are confident that methods of this nature in this domain will make dramatic strides in accuracy and utility in the foreseeable future. The implications of this warrant serious consideration from academics, policy-makers, and citizens from all areas.

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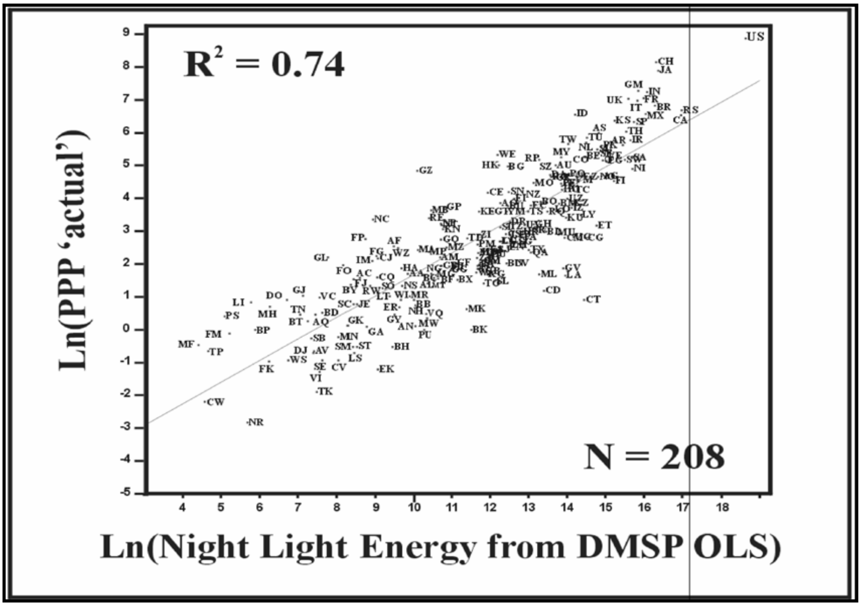
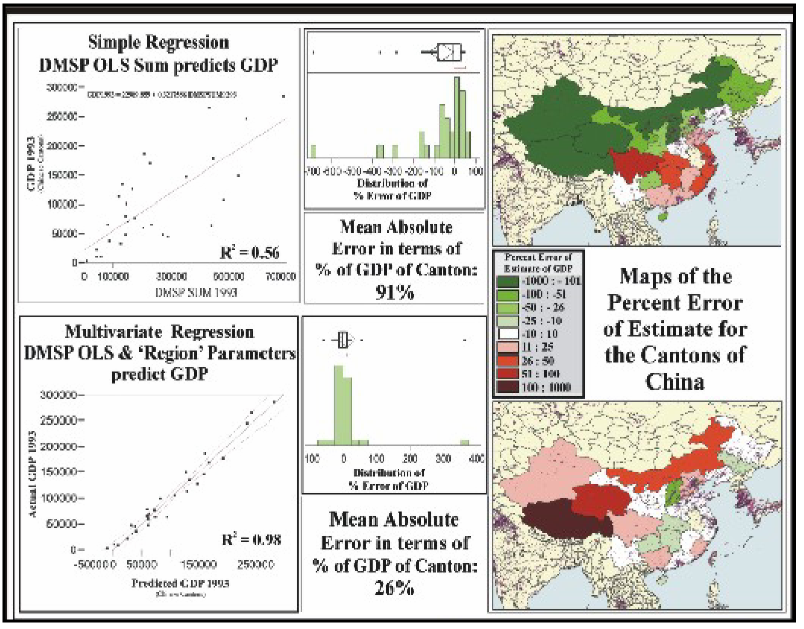


Figure 1: Simple log linear relationships between the sum of lights observed by DMSP OLS and the GDP of sub-national administration levels (Purchasing Power Parity- PPP 'actual') for India, China, Turkey and United States.



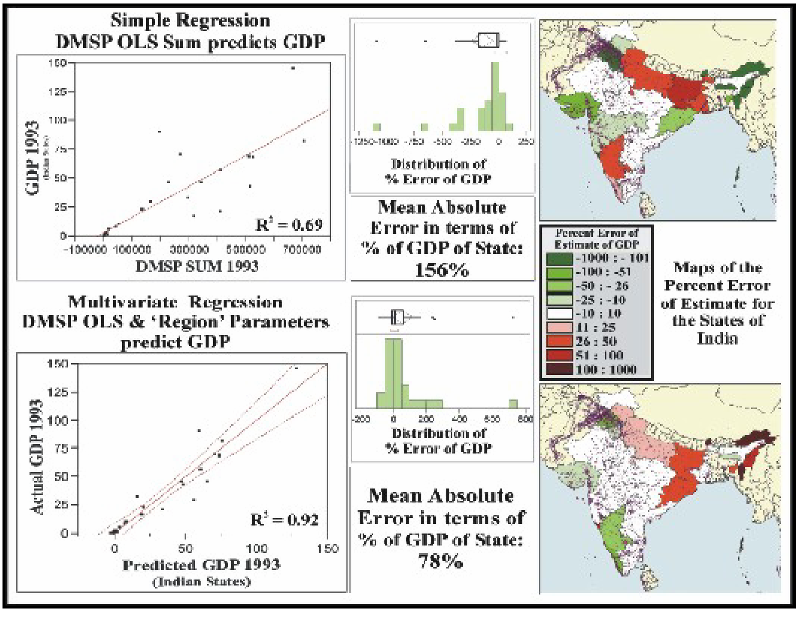


Figure 2-A: Regression model development showing the prediction of GDP using DMSP OLS and Maps of percent error of estimate for the cantons in China and states in India in 1992
(The above figures are for academic purpose only and does not represent any accurate political or geographical area of any country).

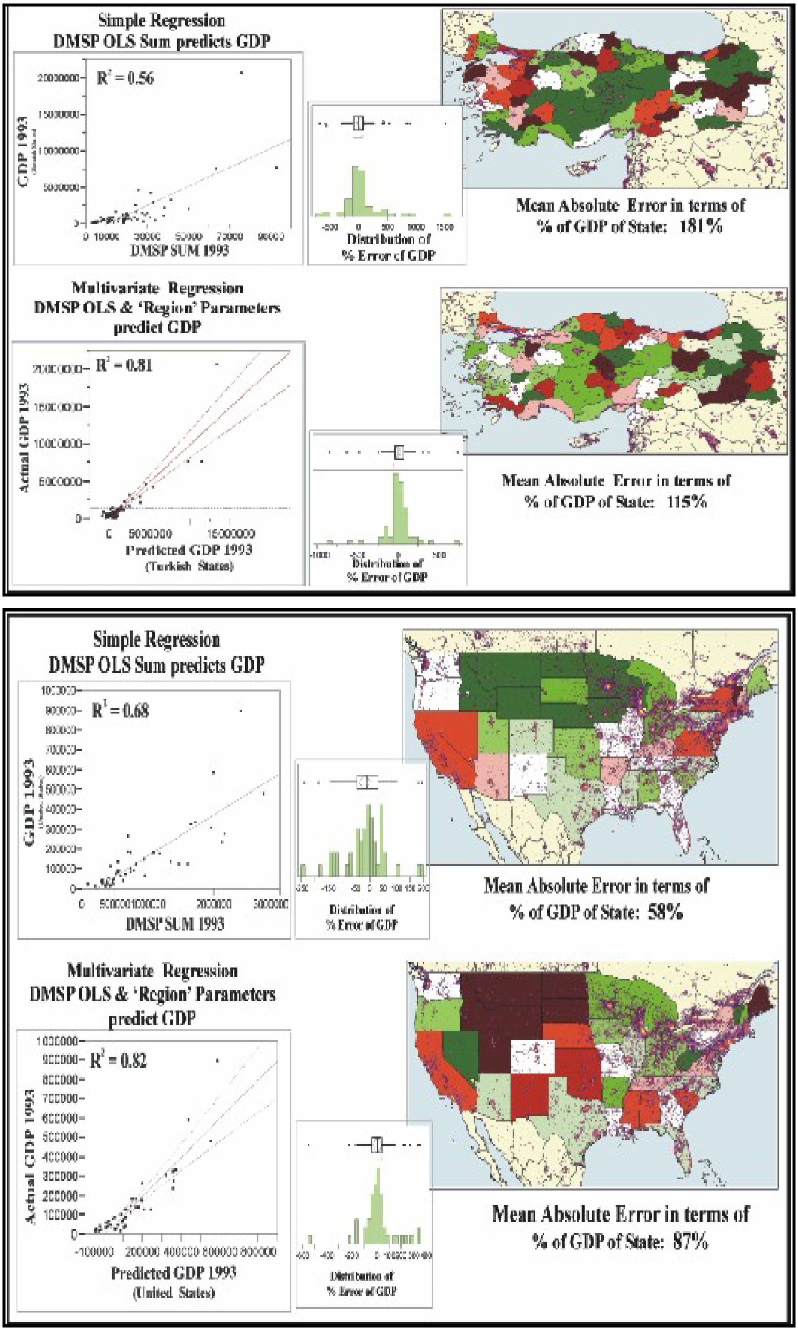


Figure 2-B: Regression model development showing the prediction of GDP using DMSP OLS and Maps of percent error of estimate for the states in Turkey and United States in 1992
(The above figures are for academic purpose only and does not represent any accurate political or geographical area of any country).

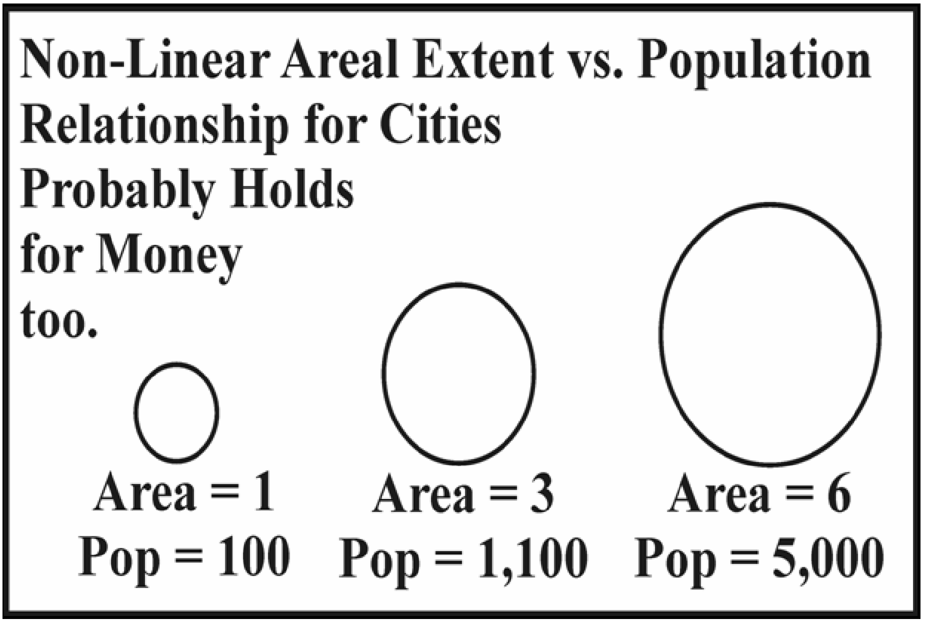


Figure 3: Non-linear areal extent versus population relationship for cities.

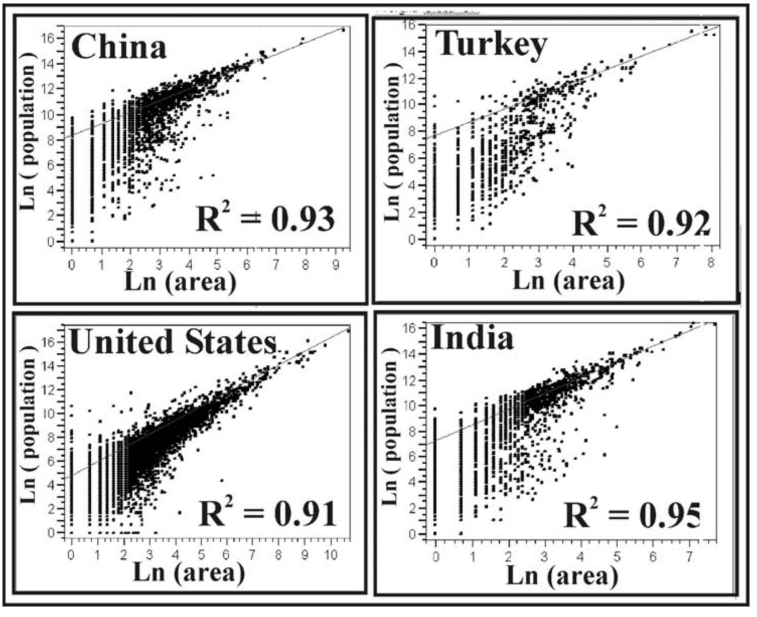


Figure 4: Simple log linear relationship between areal extent of urban areas and population for China, India, Turkey, and the United States

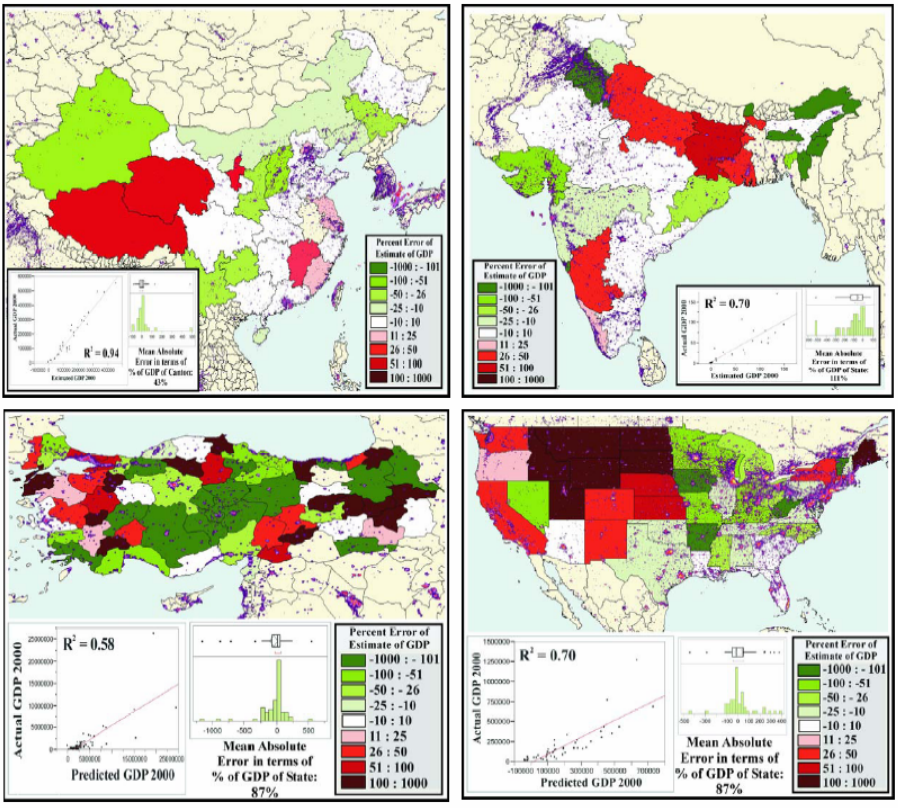


Figure 5: Percent error of estimate of GDP of the states in India, Turkey and United States and the Chinese cantons using DMSP OLS 2000 nighttime image composition (simple light summing)

(The above figures are for academic purpose only and does not represent any accurate political or geographical area of any country).

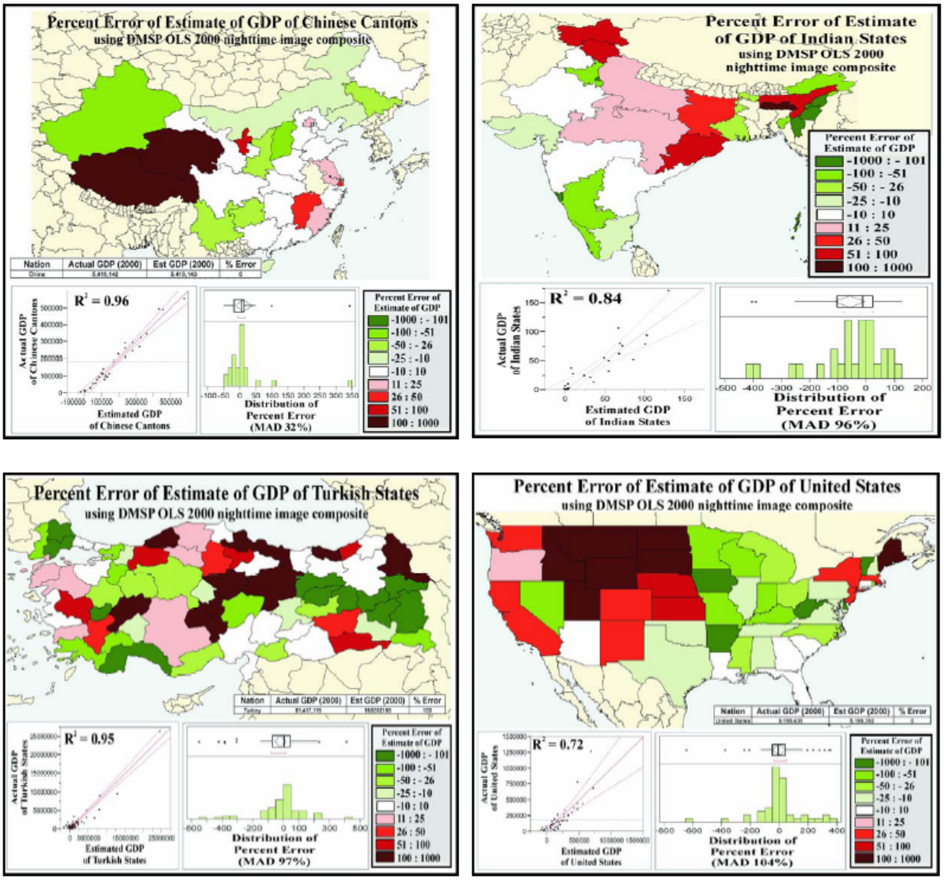


Figure 6: Percent error of estimate of GDP of the states in India, Turkey and United States and the Chinese cantons using DMSP OLS 2000 nighttime image composition (urban population estimation)

(The above figures are for academic purpose only and does not represent any accurate political or geographical area of any country).