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Informal Economy and Remittance Estimates of India Using Nighttime Imagery

Tilottama Ghosh
Department of Geography
University of Denver, Denver, CO 80208, USA;
Earth Observation Group, NOAA National Geophysical Data Center
Boulder, Colorado 80305 USA
Email: tghosh@du.edu, tilottama.ghosh@noaa.gov

Rebecca L. Powell
Department of Geography
University of Denver, Denver, CO 80208, USA
Email: rpowell8@du.edu

Sharolyn Anderson
Department of Geography
University of Denver, Denver, CO 80208, USA
Email: sander24@du.edu

Paul C. Sutton
Department of Geography
University of Denver, Denver, CO 80208, USA
Email: psutton@du.edu

Christopher D. Elvidge
Earth Observation Group
NOAA National Geophysical Data Center, Boulder, Colorado 80305 USA
Email: chris.elvidge@noaa.gov

Abstract

Accurate estimates of the magnitude and spatial distribution of both formal and informal economic activity have many useful applications. Developing alternative methods for making estimates of these economic activities may prove to be useful when other measures are of suspect accuracy or unavailable. This research explores the potential for estimating the formal and informal economy for India using known relationships between the spatial patterns of nighttime satellite imagery and economic activity in the United States (U.S.). Regression models have been developed between spatial patterns of nighttime imagery and Adjusted Official Gross State Product (AGSP) for the states of the U.S. The slope and intercept parameters derived from the regression models of the U.S. were blindly applied to India, resulting in an underestimation of Gross State Income (GSI) for each state and Union Territory (UT) of India because of the lower level of urbanization in India in comparison to the U.S. However, a comparison of estimated GSI from the nighttime lights image and the official Gross State Product (GSP) of the states and UTs of India indicates a high correlation between them (r = 0.93). The different levels of urbanization (i.e. percent of population in urban areas) in the U.S. and India are used to adjust the Estimated Gross Domestic Income (EGDI) by multiplying by the ratio of the percentage of the population in urban areas for the two countries. This gives the Adjusted Estimated Gross Domestic Income of India (AEGDI), which is compared with the official Gross National Income (GNI) estimates of India's states and UTs. The results suggest that the magnitude of India's informal economy and the inflow of remittances are 150 percent larger than their existing official estimates in the GNI.

KEYWORDS: *Nighttime satellite imagery, Informal economy, Gross Domestic Product and Gross National Income, Globalization, Law of allometric growth*

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1. INTRODUCTION

Measuring and understanding the spatial distribution of economic activity is a subject of considerable interest to social scientists. Globalization of the world economy in the 1990s caused the national economies of developing countries to become an integral part of the global trading community. The processes of liberalization, privatization and modernization associated with globalization have resulted in the 'informalization' of the workforce (Standing, 1999). In this arrangement, people are hired in non-standard jobs or atypical jobs with hourly wages and few benefits or into piece-rate jobs with no benefits. Production of goods and services are sub-contracted to small scale informal units and industrial outworkers (Portes et al., 1989; Chen, 2003).

The growth of informal economy has also been a consequence of the rapid population increase and rural-urban migration in the developing countries. With the shrinking of employment in the formal sector, the informal economy remains the only source of livelihood for increasing numbers of urban poor (Chatterjee, 1999). Moreover, experience from the past has shown that employment in the informal economy tends to expand during times of economic stagnation or economic recession (Tokman, 1992). This is because as private or public enterprises are downsized or closed, workers who lose their jobs turn to the informal economy for survival (Chen, 2003). The present global economic crisis is resulting in a large scale unemployment situation and is likely to contribute to an intensification of employment in the informal economy (NCEUS, 2008).

India, being one of the fastest developing countries of the world, is an integral part of the world globalization and has enjoyed the benefits of globalization through rapid economic growth. According to the National Sample Survey (NSS) 55^{th} Round, in 1999-2000, approximately 90 percent of the employed population in India was employed informally (without any employment, social or work security) and comprised of most of the poor and vulnerable population who did not have even Rs.20 a day to meet their consumption expenses. They could not enjoy the benefits of globalization (NCEUS, 2007). In the global perspective, the sheer size and continuing growth of the informal economy in India adds to its significance and need for investigation. The Government of India has recognized the need to ensure the welfare and well-being of the large percentage of workforce engaged in the unorganized sector and among other measures established the National Commission for Enterprises in the Unorganized Sector (NCEUS) in September, 2004, to act as an advisory body and watchdog for the informal sector.

1.1 Defining Unorganized sector and Unorganized employment

In India the terms 'organized' and 'unorganized' are used for what is internationally known as 'formal' and 'informal'. In recent years, a group of informed activists and researchers, including members of the global research policy network Women in Informal Employment: Globalizing and Organizing (WIEGO), have worked with the International Labor Organization (ILO) to broaden the 1993 international statistical definition of the 'informal sector' (adopted in the 1993 International Conference of Labor Statisticians) to incorporate certain types of informal employment that were not included in the earlier concept and definition. They extended the definition not only to include enterprises that are not legally regulated but also employment relationships that are not legally regulated or protected (Chen, 2007). NCEUS has defined the unorganized sector and unorganized or informal employment (which is consistent with the international definition as recommended by the ILO) as follows:

"The unorganized sector consists of all unincorporated private enterprises owned by individuals or households engaged in the sale and production of goods and services operated on a proprietary or partnership basis and with less than ten total workers."

"Unorganized workers consist of those working in the unorganized enterprises or households, excluding regular workers with social security benefits, and the workers in the formal sector without any employment/ social security benefits provided by the employers."

The employees with informal jobs generally do not enjoy employment security (no protection against arbitrary dismissal), work security (no protection against accidents and illness at the work place), nor social security (maternity and health care benefits, pension) (NCEUS, 2007).

The presence of informal workers is all too conspicuous in any Indian city or town. The sidewalks are lined by barbers, cobblers, waste recyclers, vendors of vegetables, fruit, meat, fish, all kinds or perishable and non-perishable items. On the narrow and wide streets cart pullers, bicycle peddlers, rickshaw pullers, bullock and horse cart drivers, compete with the cars, buses, scooters and motorcycles to make their way. Small stalls selling myriad kinds of goods are visible in every nook and corner, even in residential areas (Chen, 2003). Less visible manifestations of this process are the informal workers who work in small shops or workshops (e.g. workshops that repair bicycles and motorcycles, tan leather and stitch shoes, make and embroider garments, sort and sell cloth, paper and metal waste). The least visible informal workers are mostly women who sell or produce goods from their homes, for example, garment makers, paper bag makers, embroiderers, food processors, incense stick rollers, domestic laborers, and others (ILO, 2002).

1.2 Problems in compiling informal economy statistics

Compiling statistics on the size, composition and contribution of the informal economy towards the Gross Domestic Product (GDP) of a country is an extremely complicated exercise (Here onwards, GDP will be used to refer to aggregate economic activity within a country and Gross State Product (GSP) will be used to refer to economic activity in individual states). The main difficulty is that very few countries have undertaken regular surveys of the informal sector and only two or three countries have collected data that provide measures of informal employment outside informal enterprises. Also, there are a number of problems that hinder the international comparability of data, as countries apply different criteria for non-registration, enterprise size, and/or workplace location. Most countries exclude agriculture from their measurement of the informal sector, and some measure only the urban informal sector (Chen, 2003).

In the National Accounts Statistics of India, estimates of *GDP* for unorganized sector (excluding agriculture and allied activities) are calculated as the product of the workforce engaged in a particular activity and the gross value added per worker in the same activity. Workforce data is collected through National Sample Survey's (NSS) employment and unemployment surveys (industry-wise), and data on gross value added per worker is collected from the NSS enterprise surveys. Although informal agricultural activities are included as a distinct category in the definition of India's unorganized sector, its contribution towards *GDP* is often not computed. Again, informal employment outside of informal enterprises and outside of agriculture (workers who are sub-contracted by formal sector units and domestic workers engaged by households, such as maids, gardeners and security staff) are determined by a residual method. So, the contribution of the total informal employment (i.e., those employed in the informal sector and those employed informally in the formal sector) towards *GDP* is often difficult to estimate. Thus, the contribution of informal employment towards *GDP* is assumed to be underestimated.

1.3 Remittances and problems of estimating remittances

Remittances are the funds that the international migrants send back to their countries of origin. Remittances contribute to the Gross National Income (*GNI*) of a country, where *GNI* is the sum of *GDP* plus net receipts of compensation of employees and property income from abroad. In recent years, remittances have emerged as a major source of external financing in developing countries. The quality and coverage of data on remittances is fraught with problems. In several countries many types of formal remittance flows go unrecorded, due to weaknesses in data collection (related to both definitions and coverage) and flows through informal channels (such as unregulated money transfers or family and friends who carry cash). Remittances are frequently misclassified as export revenue, tourism receipts, nonresident deposits, or even foreign direct investment (FDI) (World Bank, 2006). Thus, it can be presumed that for India, which is the largest remittance receiving country in the world (Maimbo and Ratha, 2005), a lot of data on remittances go unrecorded and therefore underestimated in the national accounts.

1.4 Lack of reliable measurements of GNI and GDP data

Reliable measurements of the economic transactions of a nation expressed in terms of *GNI* and *GDP* are difficult to obtain because of the lack of well developed national income accounting methods and the large size of the "informal" sector, especially in developing economies (Ebener et al., 2005; Sutton et al., 2007). Official estimates of the *GNI* and *GDP* of countries can vary dramatically depending on the sources of data and the different accounting methods. A recent *New York Times* article demonstrated this when it reported that economists recognized a mistake in their estimate of the size of the Chinese economy as 4 trillion dollars more than what it really was. Their revised estimate of the size of the Chinese economy was 6 trillion dollars rather than 10 trillion dollars, due to poor choices of purchasing power parity (PPP) parameters (Porter, 2007).

The problems of measuring the economic activities of a country in terms of *GDP* and *GNI* are further compounded when information is required on the spatial and temporal changes in economic activity (Ahmad, 1994). However, estimates of the magnitude and distribution of the informal economy are important because, for countries where calculations of informal economic activities have been made, informal employment may contribute up to 25 percent of total GDP (ILO, 2002). Better estimates of informal employment could improve our understanding of the contribution of the informal economy to the total economy and its links to poverty, as well as inform the development of appropriate policies and programs for those who work in the informal economy (ILO, 2002).

1.5 Seeking alternative methods to estimate these economic variables

Remote sensing data provides a potential alternative for estimating the values of combined economic activities, as such data provide a synoptic view of the terrestrial environment and are applied extensively to map the spatial distribution of population and to examine the impact of human presence on the environment (Sutton et al., 2007). For example, the Defense Meteorological Satellite Programs Operation Linescan System (DMSP-OLS) nighttime images, which have been archived in the National Oceanic and Atmospheric Administration, National Geophysical Data Center (NOAA, NGDC), since 1994, detects sources of nighttime lights, such as city lights, forest fires, gas flare burn-off, and lantern fishing, all produced by human activities (Sutton et al., 1997). Therefore, the DMSP-OLS can serve as a proxy measure of population and correlates of population, such as economic activity and energy consumption (Doll, 2008). Nighttime imagery has been used for myriad applications, including estimation of urban populations (Welch, 1980; Welch and Zupko, 1980; Sutton et al., 2001; C.P. Lo, 2002), estimation of intra-urban population density (Sutton, 1997; Sutton et al., 2003), energy utilization or electric power consumption (Welch, 1980; Welch and Zupko, 1980; Elvidge et al.,1997; C.P. Lo, 2002), delineating urban land cover (Imhoff et al., 1997; C.P.Lo, 2002), measuring anthropogenic impervious surface area (Elvidge et al., 2007), estimating GDP at the national and sub-national level (Elvidge et al., 1997; Doll et al., 2000; C.P. Lo, 2002; Doll, 2003; Sutton et al., 2007), mapping marketed and non-marketed economic activity (Sutton and Costanza, 2002), estimation and mapping of CO_2 emissions (Doll et al., 2000), mapping ‘exurban’ areas (Sutton et al., 2006), mapping nocturnal squid fishing (Rodhouse et al., 2001), and mapping fire and fire-prone areas (Cova et al., 2004).

Because of the problems associated with estimating the magnitude and spatial distribution of economic activity, we have explored an alternative method for estimating the values of economic activities in India using known relationships between the spatial patterns of nighttime satellite imagery and economic activity in the U.S. Using the arguably more reliable measures of *GSP* for the states of the U.S. and assuming the contribution of the informal economy towards *GSP* in the U.S. to be approximately 10 percent (Mattera, 1985; Investor’s Business daily, 1998; Losby et al., 2002; McTague, 2005), we developed a model for estimating the Gross State Income (*GSI*) of the 48 contiguous states of the U.S. The model was then used to estimate the *GSI* of the states and Union Territories (UTs) of India and results were compared to the official *GSP* and *GNI* estimates, informal economy and remittances to estimate the contribution of the informal economy and remittances towards the *GNI* of India.

2. METHODS

2.1 Data used

Radiance calibrated nighttime satellite imagery data

Proxy measure of economic activity for India and the United States were based on the global radiance-calibrated ‘city lights of the world’ data product. These data were derived from hundreds of orbits of the DMSP-OLS (Elvidge et al., 1999). Different gain settings of the F12 and F15 satellites were used to make the radiance calibrated image of 2000-2001. The different gain settings were normalized to the 55 decibel (dB) gain setting of F15. The radiance value per digital number (DN) detected in the data acquired at the gain of 55 dB was 1.35×10^{-10} watts/cm^2/sr and the saturation radiance was 8.54×10^{-9} watts/cm^2/sr. The range of the radiance value of the image is 0 watts/cm^2/sr (either because there was no coverage or no data) to 6.73×10^{-7} watts/cm^2/sr (4968 DNs). The data are referenced by latitude/longitude World Geodetic System (WGS 1984) coordinates. The radiance calibrated nighttime image was re-projected from geographic coordinates to the Mollweide Equal Area projection for extracting correct area information for all areas of the earth, from the equator to the poles (Figure 1). This was necessary as area estimates of the lit urban regions for the analysis were acquired from the DMSP-OLS image.

LandScan population data

The LandScan population dataset for the year 2000 was used to estimate population of the demarcated urban areas in this study. It comprises a world population database reporting population count per cell compiled on 30 arc-second grids. It was developed as part of the Oak Ridge National Laboratory (ORNL) Global Population Project for estimating ambient populations at risk. This dataset has been developed by apportioning census counts (at sub-national) level to each grid cell using likelihood coefficients based on proximity to roads, slope, land cover, and other information. The data are referenced by latitude/longitude (WGS 1984) coordinates (Figure 2) (Landscan, 2000).

Official estimates of the *GNI, GDP* and *GSP* data

Gross Domestic Product (*GDP*) is the value of all final goods and services produced within the borders of a country’s economy in a year, i.e., the aggregate economic activity within the country. *GDP* at the state level is the Gross State Product (*GSP*). In other words, *GSP* refers to economic activity in individual states of a country. Gross National Income *(GNI)* is the sum of *GDP* plus net receipts of compensation of employees and property income from abroad. The inconsistencies between different *GDP* and *GNI* estimates for the U.S. and India that are derived from different sources and/or through the application of different computing methods become conspicuous in Tables 1 and 2. For example, the U.S. *GDP* estimates range between U.S. $9,749 billion and 9,883 billion, while India *GDP* estimates range between U.S. $378 billion and Purchasing Power Parity (PPP) U.S. $2,474 billion. This variation in the estimates underlines the importance of this study, which aims to develop an independent and standardized methodology to estimate the economic activities of a country.

GDP estimates for the U.S. for the year 2000 were obtained from the U.S. Bureau of Economic Analysis (BEA, 2000) and from the World Development Report, 2002 (World Bank, 2002). The *GNI* estimate was obtained from the World Development Report, 2002 (World Bank, 2002) and the second *GNI* estimate was calculated by multiplying the *GNI* per capita and Mid-2000 population data, available from the 2000 World Population Data Sheet (Population Reference Bureau, 2000).

For India, the *GDP* estimate for the year 2000 was obtained from the Central Statistical Organization (CSO, 2000). The estimate was in lakhs of rupees. In order to show the disparity in the values because of the use of different conversion methods, the *GDP* estimate was converted into U.S. dollars on the basis of the official exchange rate for 2000 as well as the PPP conversion factor (i.e., local currency units to international dollar) for 2000. PPP is defined as the number of units of a country's currency required to buy the same amount of goods and services in the domestic market as one dollar would buy in the United States (World Bank, 1994). The *GNI* estimate for India was also obtained from the CSO and was also converted on the basis of the official exchange rate, as well as the PPP conversion factor. Additional *GNI* and *GDP* estimates were also obtained from the World Development Report 2002 (World Bank, 2002) and were converted into PPP U.S. $ using the PPP conversion factor. A third *GNI* estimate of India was also calculated from the 2000 World Population Data Sheet by multiplying the *GNI*/capita and the Mid-2000 population data (Population Reference Bureau, 2000).

The *GSP* for each U.S. state was obtained from the U.S. Bureau of Economic Analysis (BEA, 2000). The *GSP* of the U.S. states do not include the contribution of the informal economy (BEA, personal communication, January 15, 2008), and thus were adjusted by adding 10 percent of *GSP* to the *GSP* of each state, a statistic we refer to as Adjusted Official Gross State Product ($AGSP_{US_i}$) (Table 5, Column 2). For India, the *GSP* estimates for each state/UT for the year 2000 were obtained from the CSO (CSO, 2000). The *GSP* estimates which were in lakhs of Rupees were converted into PPP US dollars by applying the PPP conversion factor (PPP U.S. $ GSP_{Ind_i}) (Table 6, Column 2).

In spite of these discrepancies in reported economic indicators, the adjusted *GSP* estimates ($AGSP_{US_i}$) derived from the U.S. Bureau of Economic Analysis were assumed to be the most reliable official estimates of *GSP* for any nation in the world, as the U.S. has the financial and technological resources to conduct elaborate and extensive economic surveys, which developing countries often lack (Min, 2008, forthcoming). Our subsequent analysis was based on the $AGSP_{US_i}$ (Table 5). Also, since the PPP values are the standard used for international comparisons, the PPP U.S. $*GNI* estimate of India (in bold in row 3 of Table 2) and the PPP U.S. $ GSP_{Ind_i} (Table 6) were used to facilitate comparison of results.

Official estimates of the informal economy and remittances of India

The estimate of the contribution of the informal economy to total *GDP* of India for the year 2000 was obtained from the CSO (CSO, 2000). According to National Accounts Statistics document, 1999-2000, the contribution of the unorganized sector (excluding agriculture and allied activities) towards the Net Domestic Product (*GDP* – depreciation) in 2000 was PPP US $1,115 billion. This is equivalent to approximately 57 percent of India's *GDP* for 2000.

The estimate of the total flow of remittances into India for the year 2000 was obtained from World Bank (World Bank, 2000). The total remittance flow into India for the year 2000 was estimated to be PPP US $13 billion, approximately 0.6 percent of India's *GNI* for 2000.

2.2 Data analysis – Overview

A brightness threshold was selected to delineate the lit urban regions of the states of the U.S. on the DMSP-OLS nighttime image. Area and population of the lit urban regions were aggregated to the state level (A_{US_i} and P_{US_i} in Table 4). A model was developed based on the law of allometric growth to estimate population of the lit urban regions demarcated by the brightness threshold (Stage 1 in Figure 3, P'_{US_i} in Table 4). In the next step (Stage 2 in Figure 3), a multiple regression model was developed to estimate Gross State Income of the U.S. states ($EGSI_{US_i}$ in Table 4) on the basis of the (1) estimated urban population of each state (from Stage 1), (2) sum of light intensity value of all lights above zero for each state (S_{US_i} in Table 4), and (3) adjusted *GSP* of each U.S. state ($AGSP_{US_i}$ in Table 4). Next (Stage 3 in Figure 3), the same threshold developed in Stage 1 was used to demarcate the urban areas of the states/UTs of India (A_{Ind_i} in Table 4). Urban area was determined, and the 'U.S. equivalent population' of the urban regions was estimated using the model developed for the U.S. in Stage 1 (P'_{Ind_i} in Table 4). The multiple regression model developed for the U.S. in Stage 2 was used to estimate the Gross State Income of each Indian state/UT (Stage 4 in Figure 3, $EGSI_{Ind_i}$ in Table 4). $EGSI_{Ind_i}$ for each state was summed to get the Estimated Gross Domestic Income ($EGDI_{Ind}$) for the whole of India. The $EGDI_{Ind}$ was then multiplied by the ratio of percentage urban population in the U.S. to that of India (US_{URB}/Ind_{URB}). This is the Adjusted Estimated Gross Domestic Income of India (Stage 5 in Figure 3, $AEGDI_{Ind}$ in Table 4). The underestimation of the informal economy and remittances in the official GNI estimates (GNI_{Ind} in Table 4) was calculated by subtracting the GNI_{Ind} from the $AEGDI_{Ind}$ (Stage 6 in Figure 3, $UIER$ in Table 4).

Definitions and abbreviations for all the economic variables which were developed and used in different stages of the analysis are presented in Table 4.

2.3 Basic assumptions of the model

The model developed to estimate the Gross State Income for each Indian state/UT ($EGSI_{Ind_i}$), Gross Domestic Income ($EGDI_{Ind}$), informal economy and remittances for India was trained using the most reliable $AGSP_{US_i}$ for each U.S. state and was based on the following assumptions:

- Urban populations can be estimated based on urban area measured from nighttime lights.
- Because spatially disaggregate Gross State Product (GSP) data are either unavailable or simply do not exist, estimates of urban populations can be used as a proxy measure of the value of economic activity.
- Economic activity associated with urban populations creates the same spatial patterns of nighttime lights in India as in the United States (i.e., there are no cultural, socio-economic, or demographic 'correction factors').
- Spatial patterns of GDP per capita and spatial patterns of distribution of income (i.e., Gini coefficients) are uniform (but not necessarily equivalent) in both the United States and India.

Consequently, a multiple regression model was developed to predict the Gross State Income of the 48 contiguous states of the U.S ($EGSI_{US_i}$). These regression parameters, were then applied to the spatial patterns of nighttime lights in India to estimate $EGSI_{Ind_i}$ for each Indian state/UT, $EGDI_{Ind}$, and subsequently the informal economy and remittances of the Indian states/UTs.

2.4 Model to predict urban population of the U.S. states – Stage 1

The aim of our analysis was to develop a model to estimate the $EGSI_{Ind_i}$, $EGDI_{Ind}$, informal economy and remittances of India based on U.S. parameters. The first stage in the model involved estimating urban population of the U.S. states (Figure 4), based on a modification of the law of allometric growth. The law of allometric growth, originally developed by biologists, states that the relative growth of an organ is a constant fraction of the state of relative growth of the total organism (Nordbeck, 1965). Taking 'y' to be the organ and 'x' to be the organism, the law of allometric growth can be expressed as:

$$y = ax^b \quad (1)$$

where, a and b are empirical constants. Taking the logarithm of both sides the linear equation is thus:

$$\ln(y) = \ln(a) + b \times \ln(x) \quad (2)$$

Based on this law of allometric growth, Tobler (1969) established that human population (taken as y) could be estimated with a high degree of accuracy by measuring the area of human settlements (taken as x) as observed from satellite photography.

$$\ln(population) = a + b \times \ln(area) \tag{3}$$

Original application of allometric growth law estimates population of individual urban settlements or cities. We modified this application as we estimated populations of the U.S. and India at the state level by aggregating the areas of urban settlements within each state.

The radiance-calibrated DMSP-OLS image of the U.S. was used to delineate the lit urban areas of each U.S. state. We experimented with different brightness thresholds on the nighttime image to determine the brightness threshold that would include urban areas with low population density. The polygons derived by the application of the different thresholds were exported onto Google Earth imagery to determine whether urban areas with low population density were included. The threshold of 20 x 1.35 x 10^{-10} watts/cm^2/sr was empirically determined as the appropriate threshold value. The same threshold was used to delineate the lit urban areas of India.

Urban populations of all lit urban areas included by applying the brightness threshold to the nighttime image of the U.S. were estimated based on the modified law of allometric growth (Nordbeck, 1965; Tobler, 1969). First, areas of the lit urban settlements of each U.S. state (A_{US_i}), which were demarcated using the threshold, were estimated. The 'thresholded' nighttime image was then used to mask the Landscan population grid in order to extract the urban populations of each U.S. state from the areas demarcated by the brightness threshold (P_{US_i}). This generated a table of urban settlements that included both area and population attributes. A log-log regression model was used to estimate urban population (P'_{US_i}) for each of the 48 contiguous U.S. states using the area and population attributes. Equation 4 shows the linear model between the natural log of the areal extent of urban areas of the U.S. states and natural log of the population of the U.S. states based on the law of the allometric growth. The regression parameters α_{1US} and β_{1US} derived through this equation were 5.10 and 1.07, respectively. Urban population of each of the 48 U.S. states was subsequently estimated by the exponentiation of the logarithmic equation (Equation 5) (Sutton et al., 2007). The regression relationship is presented in Figure 5.

$$\ln(P_{US_i}) = \alpha_{1US} + \beta_{1US} \times \ln(A_{US_i}) \tag{4}$$

$$P'_{US_i} = \exp(\alpha_{1US} + \beta_{1US} \times \ln(A_{US_i})) \tag{5}$$

2.5 Model to predict Gross State Income of the U.S. states – Stage 2

In Stage 2 (Figure 6), a multiple regression model was developed for estimating Gross State Income ($EGSI_{US_i}$) for each U.S. state based on the estimated urban populations of the 48 contiguous U.S. states from Stage 1.

The multiple regression model was based on the assumption that estimates of urban populations can serve as a proximate measure of economic activity. The estimated urban population of each of the 48 U.S. states (P'_{US_i}) and the 'sum of lights' for each U.S. state (S_{US_i}) were the predictors in the regression model (Equation 6). The 'sum of lights' (even those below the threshold level) were calculated in order to include all the economic activities, even those outside of 'urban' areas as defined by the brightness threshold. The regression equation was weighted by the Adjusted Gross State Product ($AGSP_{US_i}$) for each U.S. state so that states with higher $AGSP_{US_i}$ (like, California and New York) have a greater influence on the equation than the states with lower $AGSP_{US_i}$. The regression parameters, α_{2US}, β_{2US}, and β_{3US} were determined to be 16.11, 0.62, and 2.1 x 10 $^{-7}$, respectively. The $EGSI_{US_i}$ for each U.S. state was subsequently estimated by the exponentiation of the logarithmic equation (Equation 7).

$$\ln(AGSP_{US_i}) = \alpha_{2US} + \beta_{2US} \times \ln(P'_{US_i}) + \beta_{3US} \times S_{US_i} \quad (6)$$

$$EGSI_{US_i} = \exp(\alpha_{2US} + \beta_{2US} \times \ln(P'_{US_i}) + \beta_{3US} \times S_{US_i}) \quad (7)$$

Figure 7 presents the Actual-versus-Predicted plot for the log of the $AGSP_{US_i}$ values. When Actual ln($AGSP_{US_i}$) (i.e., official statistics) was modeled as a linear function of ln(P'_{US_i}) and S_{US_i} of the states of the U.S., the resulting model accounted for 81 percent ($R^2 = 0.81$) of observed variance in the Actual ln($AGSP_{US_i}$) ($P < 0.0001$).

A plot of the $AGSP_{US_i}$ and $EGSI_{US_i}$ values of the U.S. states is shown in Figure 8. The correlation coefficient (Pearson's r) between officially reported and modeled estimates is 0.84, indicating a strong association between the two variables. The modeled $EGSI_{US_i}$ values are close to the official $AGSP_{US_i}$ values for most of the states, with the exception of Texas, New York and California. $EGSI_{US_i}$ was overestimated for Texas and underestimated for New York and California (Ghosh et al., 2009).

2.6 Estimating the 'U.S. equivalent urban population' of the states and Union Territories (UTs) of India – Stage 3

In Stage 3, the regression parameters of the U.S. derived from Stage 1 were applied to estimate the 'U.S. equivalent urban population' of the states/UTs of India (Figure 9).

We used the same U.S. brightness threshold to delineate the lit urban areas of India in order to apply the parameters we had estimated for the U.S. and to conform to our assumption that economic activity creates the same spatial patterns of light in the U.S. and in India. Figure 10 shows how well the U.S. brightness threshold demarcates the four largest metropolitan cities in India and the urban areas surrounding them.

Area of the urban extent for each Indian state/UT demarcated by the brightness threshold was estimated from the nighttime image (A_{Ind_i}). The regression parameters derived for the U.S. in Stage 1 were applied to India's urban areas to obtain the 'U.S. equivalent population' for the urban areas of each Indian state/ UT (P'_{Ind_i}) (Equation 8).

$$P'_{Ind_i} = \exp(\alpha_{1US} + \beta_{1US} \times \ln(A_{Ind_i})) \qquad (8)$$

2.7 Estimating Gross State Income of the states and Union Territories (UTs) of India – Stage 4

In Stage 4 (Figure 11), the Gross State Income for each Indian state/UT was estimated. The same regression model which was developed for the U.S. was used to estimate the $EGSI_{Ind_i}$ of each Indian state/UT using the 'sum of lights' for each Indian state/UT (S_{Ind_i}) and estimated urban population (P'_{Ind_i}) of each Indian state/UT (Equation 9).

$$EGSI_{Ind_i} = \exp(\alpha_{2US} + \beta_{2US} \times \ln(P'_{Ind_i}) + \beta_{3US} \times S_{Ind_i}) \qquad (9)$$

$EGSI_{Ind_i}$ of each Indian state/UT derived from the DMSP-OLS image was assumed to include the formal economy, informal economy, and the estimates of the remittance inflow into India. $EGSI_{Ind_i}$ should therefore be compared to the official GNI values; however GNI values are not available at the state level. Additionally, although India is the largest remittance receiving country in the world, the contribution of the remittances reported by the World Bank, 2000 is only 0.6 percent of the official GNI

that is reported by CSO for the year 2000. Thus, we concluded that the $EGSI_{Ind_i}$ (which we assumed to include remittances) and the official GSP values (GSP_{Ind_i}, which do not include remittances) were comparable. Modeled $EGSI_{Ind_i}$ is plotted against the official GSP_{Ind_i} for each Indian state/UT (Figure 12), indicating that $EGSI_{Ind_i}$ was slightly overestimated for seven Indian states/UTs and was underestimated for the rest. The correlation coefficient (Pearson's r) of the official GSP_{Ind_i} versus $EGSI_{Ind_i}$ is 0.93, indicating a strong association between the two variables.

2.8 Estimating the magnitude and spatial distribution of the informal economy and remittances of India and comparing it to the published values – Stages 5 and 6

The final stages in the analysis involved estimating the magnitude of informal economy and remittances of India. The $EGSI_{Ind_i}$ values derived from nighttime lights data for each state/UT were summed to estimate Gross Domestic Income ($EGDI_{Ind}$) for all of India. $EGDI_{Ind}$ was compared to the official GNI value of India (GNI_{Ind}). Both $EGDI_{Ind}$ and GNI_{Ind} include the formal economy, informal economy and the inflow of remittances into the economy. We assumed that remittances are included in the nighttime-lights derived $EGDI_{Ind}$ estimates because the residents of India use the money sent to them as remittances to purchase basic amenities and energy, and therefore improvement in the economy should be measureable from the nighttime lights.

The $EGDI_{Ind}$ was underestimated for India. One explanation for this may be the low level of urbanization in India (27.7 percent) in comparison to high level of urbanization in the U.S. (79.1 percent) in the year 2000 (United Nations, 2000). In order to correct for the different levels of urbanization in the U.S. and India, the ratio of percent urban population for the two countries for the year 2000 was calculated (US_{URB}/Ind_{URB}). This $EGDI_{Ind}$ was multiplied by the ratio, resulting in the Adjusted Estimated Gross Domestic Income of India ($AEGDI_{Ind}$) (Stage 5, Figure 13).

In the final stage the magnitude of the informal economy and remittances was estimated (Stage 6, Figure 14). The $AEGDI_{Ind}$ was subtracted from the official GNI_{Ind}, and this gave the predicted underestimation of informal economy and remittances ($UIER$) in the official estimates (Equation 10).

$$UIER = AEGDI_{Ind} - GNI_{Ind} \tag{10}$$

3. RESULTS

3.1 Official *AGSP* and modeled *GSI* of the U.S.

The log linear relationship between the aggregated area of urban clusters and population of the U.S. states provided estimates of the urban populations for the states of the U.S. A multiple linear regression model was trained using the $AGSP_{US_i}$, to predict economic activity based on population and extent of lights The residual percentage of each U.S. state ($\mathrm{Residual}_{US_i}$) was calculated (Equation 11, Table 5) and mapped in Figure 15 to get a clear picture of the degree to which the $EGSI_{US_i}$ was over- or under-estimated for each state.

$$\mathrm{Residual}_{US_i} = \frac{AGSP_{US_i} - EGSI_{US_i}}{AGSP_{US_i}} \times 100 \quad (11)$$

$EGSI_{US_i}$ was severely overestimated (having the highest negative residuals) for the states of Montana, North Dakota, South Dakota and Wyoming. These are also the states with the lowest official estimates of $AGSP_{US_i}$. Texas, New York and California are outliers, with $EGSI_{US_i}$ being overestimated for Texas and underestimated for California and New York (Figure 8). These are also the three states with the highest official estimates of $AGSP_{US_i}$ – California, New York and Texas, in that order. The $EGSI_{US_i}$ of Texas may have been overestimated because of the prevalence of gas flares which can be confused with urban extent on the nighttime lights imagery. The underestimation in California and New York may be due to their coastal location and the resulting constraint on urban sprawl. Sutton (2003) has suggested that the higher costs of coastal lands and the pressure to utilize coastal land intensively have probably restricted urban sprawl. This might result in smaller than expected urban area given the populations of California and New York, and thus lower the estimates of their $EGSI_{US_i}$ from the nighttime image. Elvidge et al. (1999) had observed the same outliers (Texas, California and New York) in their plot of population versus cumulative radiance from 1996-1997 radiance calibrated DMSP-OLS data and had attributed the anomalous darkness of California and New York relative to their population (and subsequently $EGSI_{US_i}$ in this analysis) to the presence of large densely populated areas in New York City and the Los Angeles Region.

3.2 Official GSP and estimated GSI of India

The residual percentages of the Gross State Product (GSP_{Ind_i}) of each of the Indian states/UTs derived from the model using U.S. parameters resulted in an overestimation of $EGSI_{Ind_i}$ for the

Union Territories of the Andaman and Nicobar Islands, Chandigarh, and Pondicherry, and for the states of Haryana, Arunachal Pradesh, Mizoram, and Goa. $EGSI_{Ind_i}$ was underestimated for all the other states/UTs, the percentages being highest for the states of West Bengal, Uttar Pradesh, Bihar, Kerala and Delhi (50- 65 percent) (Table 6, Figure 16). Because no official Gross State Product (GSP_{Ind_i}) values were available for the Union Territories of Dadra and Nagar Haveli, Daman and Diu, and Lakshadweep for the year 2000, these three Union Territories were left out of the analysis. In addition, at the applied brightness threshold, no lights were detected for the state of Sikkim and so it was left out of the analysis as well.

3.3 Estimating the magnitude of underestimation of informal economy and remittances in the official measures of GNI, informal economy and remittances of India

The $EGDI_{Ind}$ of India (sum of the $EGSI_{Ind_i}$ of each state/UT) estimated from the nighttime image was approximately U.S. $1,319 billion (Row 1 of Table 7). This figure was assumed to include the formal economy, informal economy and remittances. The official GNI of India (GNI_{Ind}) for 2000 was approximately about PPP U.S. $ 2,036 billion (CSO, 2000) (Row 3 of Table 7). Multiplying the $EGDI_{Ind}$ by 2.86, the ratio of the percent of population in urban areas of the U.S. and India (US_{URB}/Ind_{URB}), the $EGDI_{Ind}$ from nighttime lights for India increased. This gave the Adjusted Gross Domestic Income of India ($AEGDI_{Ind}$) value of U.S. $3,772 billion (Row 2 of Table 7). Subtracting the GNI_{Ind} from $AEGDI_{Ind}$ gave the predicted underestimation of informal economy and remittances in the official estimates (Row 4 of Table 7). In order to derive the magnitude of underestimation we first summed the official estimates of informal economy and remittances for the year 2000 (Row 7 of Table 7). Then, we divided the predicted value of informal economy and remittances (Row 8 of Table 7) by the sum of the official estimates of informal economy and remittances (Row 9 of Table 7). The result demonstrated that the informal economy and the inflow of remittances for India was about 150 percent larger than what was recorded in the official estimates of Gross National Income (GNI_{Ind}).

4. DISCUSSION

The radiance calibrated nighttime image of 2000-2001 and the $AGSP_{US_i}$ of each U.S. state was used to develop a regression model for estimating $EGSI_{Ind_i}$ for each of the Indian states/UTs. The $AEGDI_{Ind}$ was compared to an “official” estimate of GNI_{Ind}. Previously, when this model was applied to Mexico, results suggested that most states in Mexico have more lighting than their officially reported *GSP* would suggest. This surplus lighting was attributed to the informal economy and inflow of remittances in Mexico. The subtraction of the official *GNI* of Mexico from the estimated Gross Domestic Income (*GDI*) of Mexico provided the predicted underestimation of informal economy and remittances in the official estimates (Ghosh et al., 2009). However, application of the model for India resulted in prediction of the estimated GSI values ($EGSI_{Ind_i}$) which were closer to the official *GSP* values (GSP_{Ind_i}) of each of the Indian states/UTs of India (Figure 12); however, the $EGSI_{Ind_i}$ values were underestimated for all but seven of the states/UTs. The $EGDI_{Ind}$ value was also underestimated.

A possible cause of underestimation is the low level of urbanization in India (27.7 percent) in comparison to similar levels of urbanization in the U.S. (79.1 percent) and Mexico (74.7 percent) in the year 2000 (United Nations, 2000). Thus, the total estimated *GDI* of India was multiplied by the ratio of percentage of urban population in the U.S. to percent urban population in India and was then compared to the official values of *GNI*, informal economy and remittances. The result showed that the informal economy and the inflow of remittances of India may be about 150 percent larger than what is recorded in the official estimates of *GNI* of India. Application of the model developed for the U.S. to estimate informal economy and remittances for India and Mexico suggests that this model would work well (i.e., without adjustment) only if the countries for which the economic activities are being measured have the same levels of urbanization as the U.S.

The model developed to estimate the spatially disaggregate Gross State Incomes of the U.S. states ($EGSI_{US_i}$), and subsequently that of the states/UTs of India ($EGSI_{Ind_i}$), tends to underestimate the Gross State Incomes (*GSI*) of states with high official values of Gross State Product (*GSP*), relative to their population or relative to lit area. This was observed for the anomalous darkness of New York and California in the U.S., for Mexico City in the Mexican Republic (Ghosh et al., 2009), and for Maharashtra and West Bengal in India. Thus, while we assumed that estimated urban population from spatial patterns of light can serve as a proxy measure of economic activity we observed that in the case of states with very dense population, estimated urban population from lights tended to underestimate 'money' or economic activity in the richest states. One possible explanation for the underestimation of urban population is that population (and economic activity) is so dense in these states that urban population (and economic activity) is underestimated based on lit urban areas.

Nevertheless, this method provides an independent estimate of economic statistics for India. The method does not use any population or economic data recorded for India. Better correlations might have been obtained if we had used Indian population or economic data, but that would become circular and defeat the purpose of developing an independent methodology for estimating economic statistics.

Worldwide, collection of official data are often hindered by the differences in the bureaucratic capacity of states, the economic and political situations in countries, the inconsistency of data record keeping practices, and the integrity and sincerity of state officials who are engaged with data collection (Min, 2008, forthcoming). These shortcomings in the collection of official data underscore the importance of developing an independent method of estimating economic activity. Results derived from our analysis using the spatial pattern of lights on the DMSP-OLS satellite-derived data provide an objective estimate of economic activity. Moreover, we provide a standardized methodology for estimating economic activities of all countries of the world, as well as the potential for measuring disaggregate economic activity at the sub-national level.

5. CONCLUSION

This research explores an innovative method for estimating the location and magnitude of *GSP, GDP*, the informal economy and remittances for the lower-income country of India (World Bank, 2002). The model is developed on the basis of the spatial patterns of nighttime satellite imagery and is trained by using the Adjusted Official Gross State Product ($AGSP_{US_i}$) for the U.S. states. The result obtained by multiplying the $EGDI_{Ind}$ of all the states and UTs of India by the ratio of percent urban population in the U.S. and India suggests that if the U.S. and India had the same levels of urbanization or same percentage of lit urban areas, the informal economy and inflow of remittances in India could have been said to be approximately 150 percent larger than what is officially recorded in the published official estimate of GNI.

However, this method is clearly still in the 'exploratory' stage. Our initial results suggest that further research using other countries, finer resolution imagery, and more accurate spatially disaggregate economic numbers will improve the validity of this approach. The increased spatial, spectral and radiometric resolution of future and potential nighttime satellite missions (e.g., VIIRS, Visible Infrared Imaging Radiometer Suite and Nightsat) (Elvidge et al., 2007) may dramatically improve these methods. Moreover, if we could obtain reliable spatially disaggregate *GSP* values for a sample of countries at different levels of development, instead of depending on the *GDP* estimates of a single developed country; we could potentially build separate models for Upper-, Middle- and Low-Income countries. This would perhaps generate improved, spatially explicit estimates of *GSP*, *GDP*, informal economy, and remittances for countries at different levels of development.

The global economic recession will cause more and more people to join the informal workforce in India in the coming years. The difficulties associated with collecting informal economic data and the lack of international standards to compare data on informal economy hinders the proper estimation of informal economy. Many of these problems can be overcome by developing simple and independent methods for estimating and mapping economic activity.

Considering the continuous growth of population, the ever-changing economy in the era of globalization, the instability associated with informal economic activity and unrecorded remittances, we can anticipate that there will always be an issue with regards to the credibility of the official estimates of informal economic activity and remittances. Therefore, models derived from nighttime imagery may prove useful for estimating population distribution and associated socio-economic variables for decades to come. This may help economists and policy makers understand the economic situations of countries, detect the shortcomings in economic structures, improve employment opportunities, reduce poverty and undertake other constructive economic development policies.

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Figures and Tables

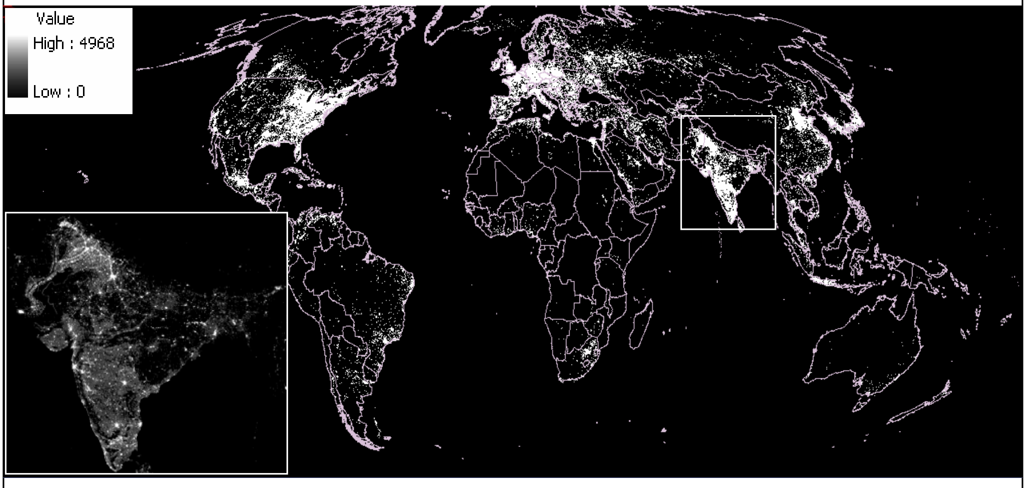

Figure 1. Radiance-calibrated nighttime image of 2000-2001, India on the inset.

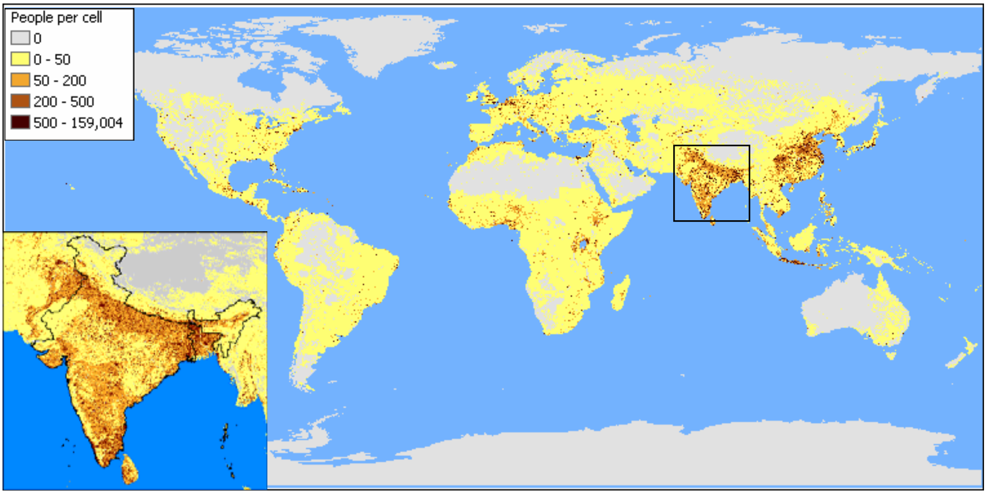

Figure 2. Landscan Population Data, 2000, India on the inset.

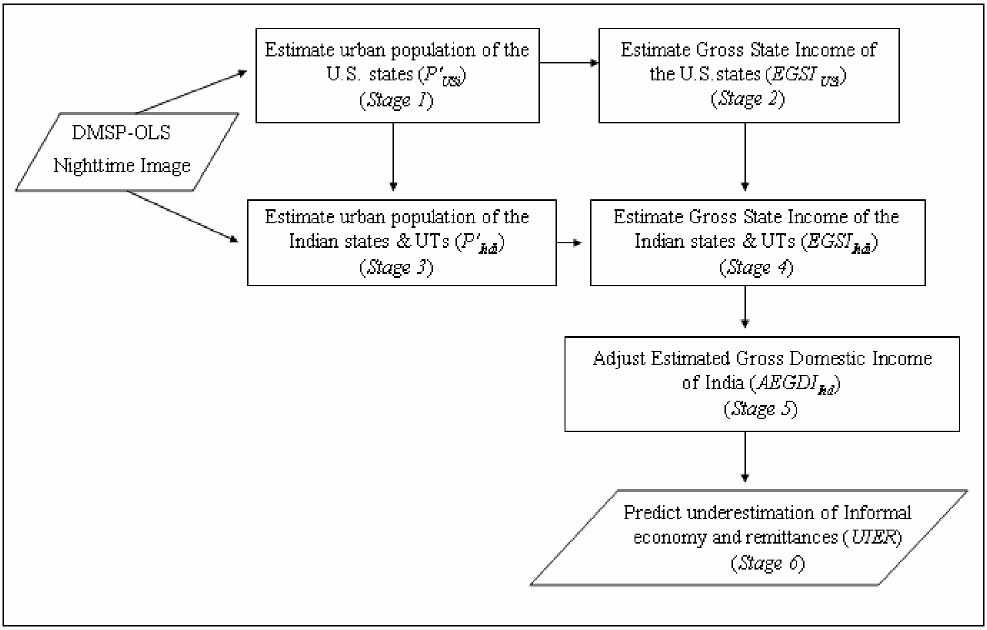

Figure 3. Overview of the model to predict the underestimation of informal economy and remittances in India's official GNI measure.

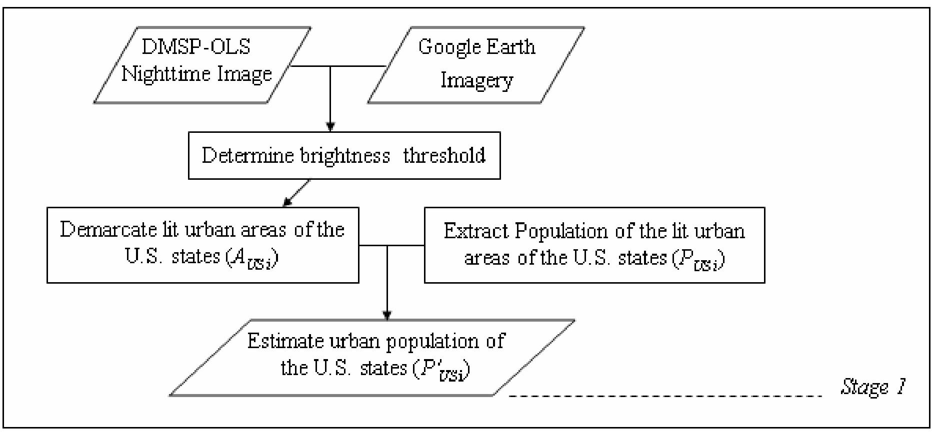

Figure 4: Stage 1 of the model: outputs are Estimated urban population of the U.S. states and the corresponding regression model parameters used to estimate the urban population of India in Stage 3.

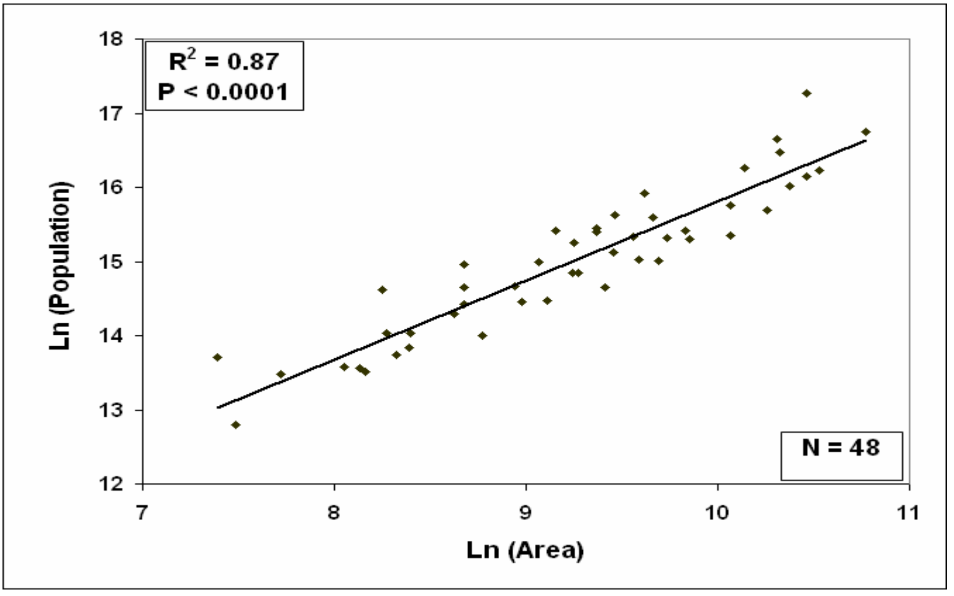

Figure 5: The log-log linear regression model of urban area and urban population for the U.S. states

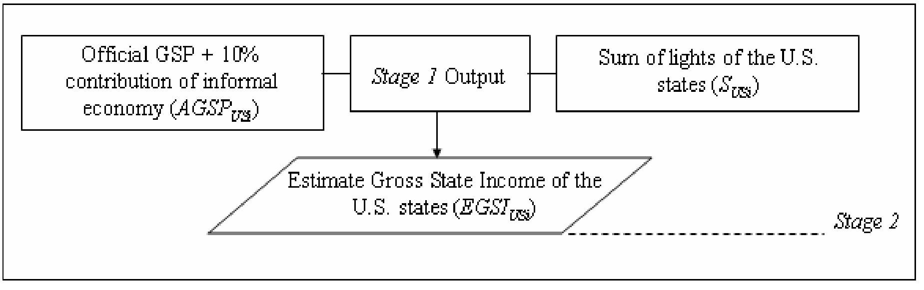

Figure 6. Stage 2 of the model: outputs are Estimated Gross State Income of the U.S. states and multiple regression model parameters used to estimate the Gross State Income of the Indian states and UTs in Stage 4 of the model.

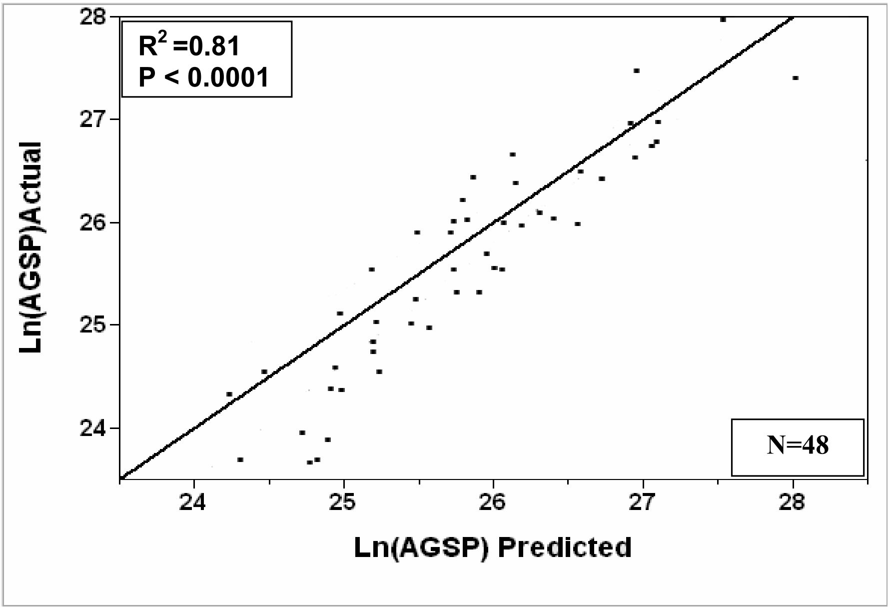

Figure 7. The actual versus predicted plot of the ln(*AGSP*) values of the U.S. states derived from the multiple regression model in which natural log of the estimated urban population and 'sum of lights' were the predictor variables.

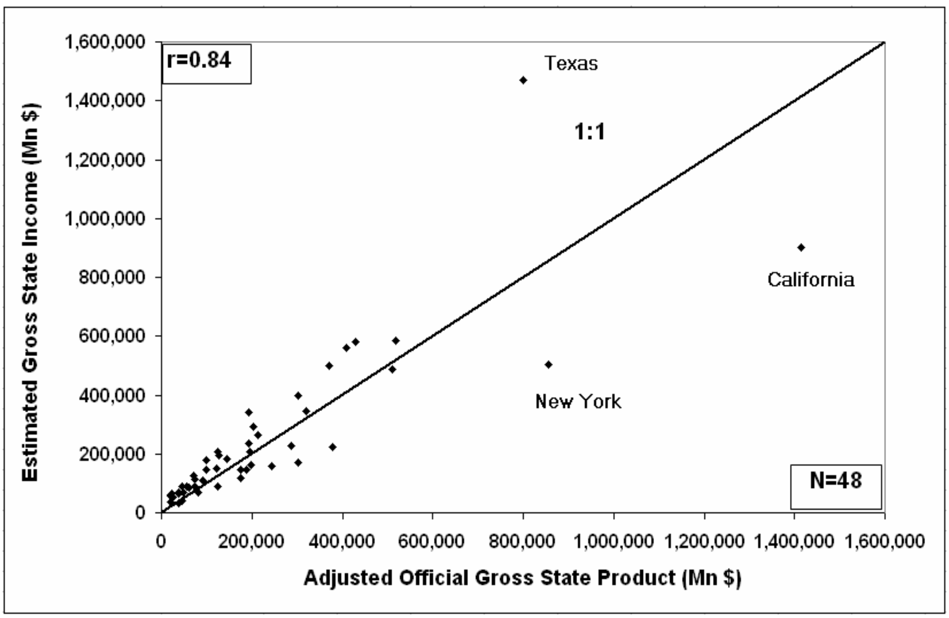

Figure 8. Official $AGSP_{US_i}$ versus Modeled $EGSI_{US_i}$ values for the U.S. states

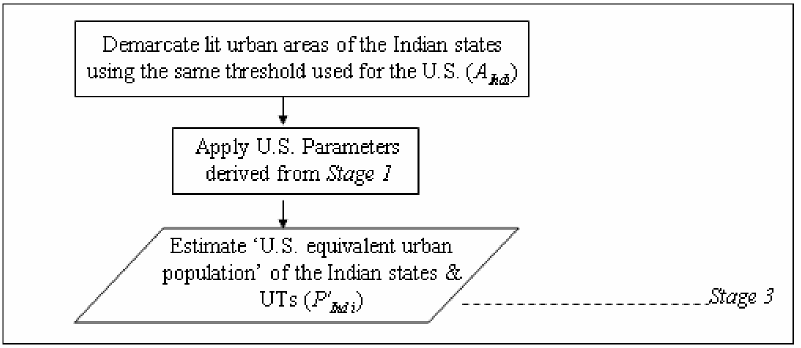

Figure 9. Stage 3 of the model: output is Estimated 'U.S. equivalent urban Population' of the Indian states and UTs using the U.S. regression parameters derived from Stage 1

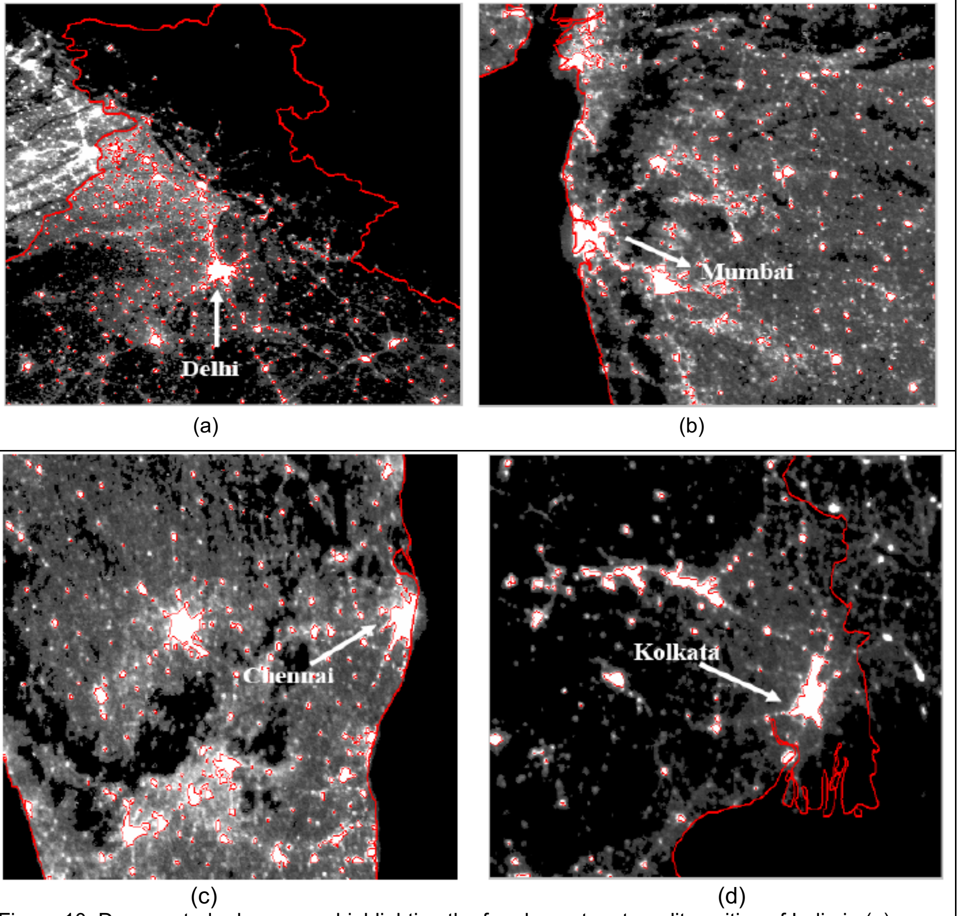

Figure 10: Demarcated urban areas highlighting the four largest metropolitan cities of India in (a) Northern, (b) Western, (c) Southern, and (d) Eastern India using the U.S. brightness threshold

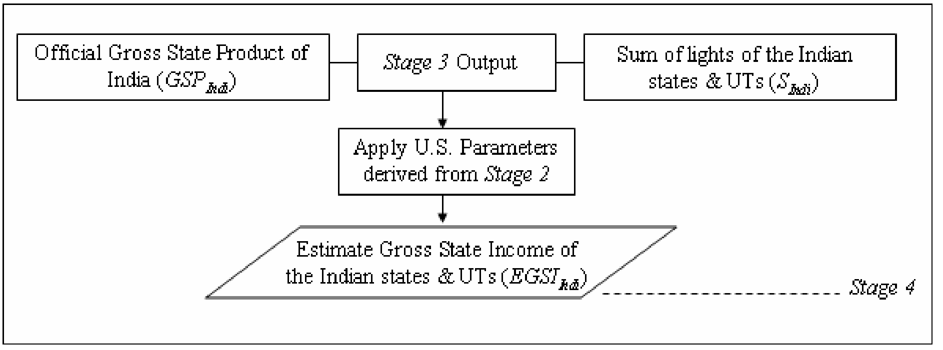

Figure 11. Stage 4 of the model: output is Estimated Gross State Income of the Indian states and UTs using the U.S. regression parameters derived from Stage 2

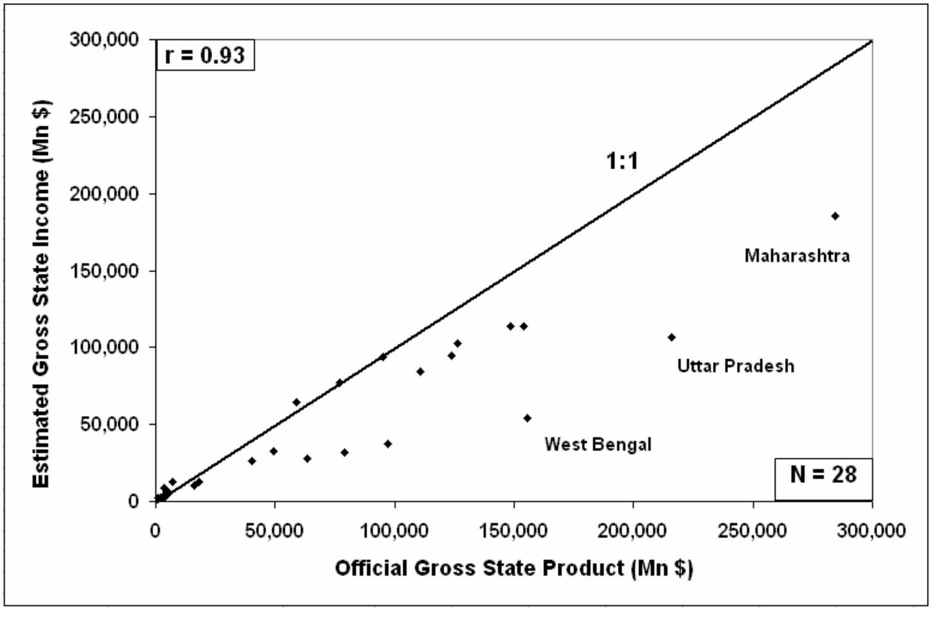

Figure 12. Official GSP_{Ind_i} versus Modeled $EGSI_{Ind_i}$ values for the Indian states and Union Territories

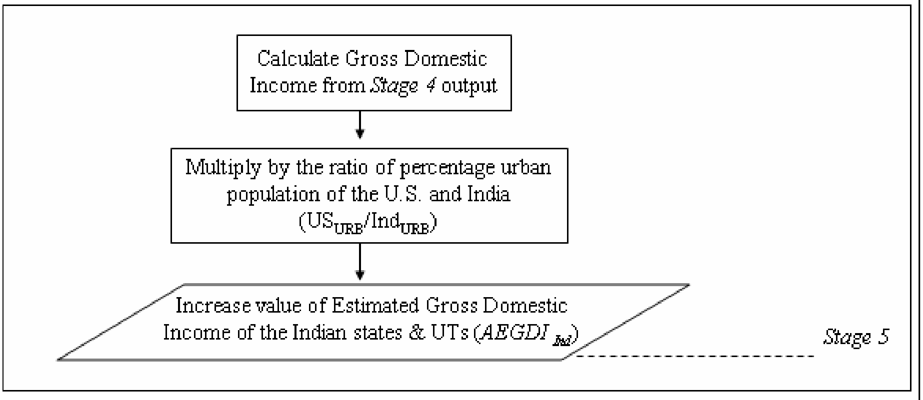

Figure 13. Stage 5 of the model: output is Increased value of Estimated Gross Domestic Income for all of India.

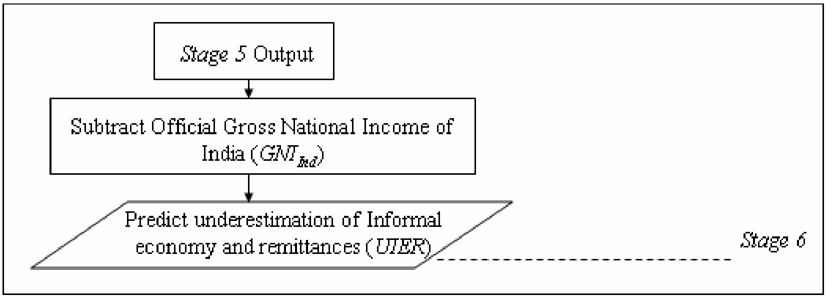

Figure 14. Stage 6 of the model: output is predicted underestimation of informal economy and remittances in the official GNI estimates of India

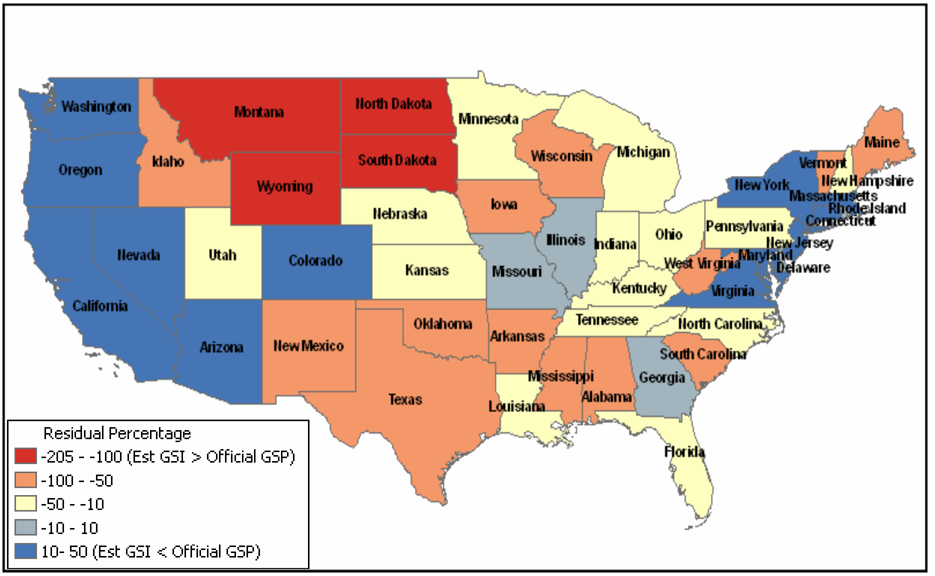

Figure 15: Map of Percentage Residual Gross State Product for the states of the U.S.

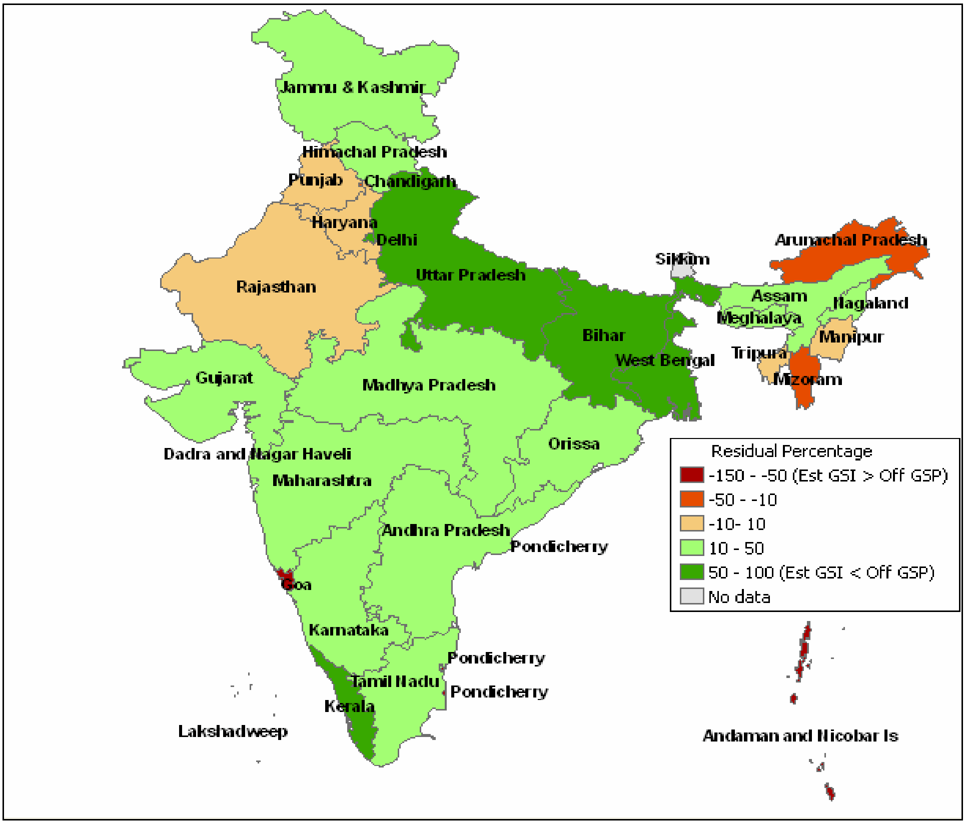

Figure 16: Map of Percentage Residual Gross State Product Map for the states and Union Territories of India

Table 1: Comparison of the GNI and GDP data for the United States from different sources

Row no.	Estimate	Year	Source	Conversion techniques and Currency units	Value
1	GNI	2000	World Dev. Report 2002	Atlas method- using 3 year average exchange rate	$ 9,646 billion
2	GNI	2000	Population Reference Bureau	In US Dollars	$ 8,059 billion
3	GDP	2000	World Dev. Report 2002	Average official exchange rate of that year	$ 9,883 billion
4	GDP	2000	US Bureau of Economic Analysis	Current US$	$ 9,749 billion

Table 2: Comparison of the GNI and GDP data for India from different sources

Row no.	Estimate	Year	Source	Conversion techniques and Currency units	Value
1	GNI	2000	CSO	In Indian Rupees	17,711 billion
2	GNI	2000	CSO	In terms of exchange rate US Dollars	$ 394 billion*
3	**GNI**	**2000**	**CSO**	**PPP US Dollars**	**$ 2036 billion***
4	GNI	2000	World Dev. Report 2002	Atlas Method - using three year average exchange rate	$ 471.2 billion
5	GNI	2000	World Dev. Report 2002	PPP US Dollars	$ 2432 billion▲
6	GNI	2000	Population Reference Bureau	In US Dollars	$ 441 billion
7	GDP	2000	CSO	In Indian Rupees	16,981 billion
8	GDP	2000	CSO	In terms of exchange rate US Dollars	$ 378 billion ♦
9	GDP	2000	CSO	PPP US Dollars	$ 1,952 billion ♦
10	GDP	2000	World Dev. Report 2002	Average official exchange rate of that year	$ 479 billion
11	GDP	2000	World Dev. Report 2002	PPP US Dollars	$ 2,474 billion#

Notes: * Calculated from row 1 in Table 2
▲ Calculated from row 4 in Table 2
♦ Calculated from row 7 in Table 2
Calculated from row 10 in Table 2

Table 3: Reported value of the Informal economy data for India

	Informal Economy (2000)
In Indian Rupees	9,703 billion
In PPP US Dollars	1,115 billion

Source: Central Statistical Organization, National Accounts Statistics

Table 4: Abbreviations and definitions of the different economic variables used in the text

Abbreviations	Definitions
A_{US_i}	Area of the lit urban areas of each U.S. state demarcated by the brightness threshold of 20 x 1.35 x 10 $^{-10}$ watts/cm^2/sr
P_{US_i}	Population (extracted from the Landscan dataset) of the lit urban areas for each US state (*i*), demarcated by the brightness threshold
P'_{US_i}	Estimated urban population for each US state (*i*) demarcated by the brightness threshold
S_{US_i}	'Sum of lights' of the lit areas for each US state *(i)*
$AGSP_{US_i}$	Adjusted Official Gross State Product for each US state *(i)*; official GSP is inflated by 10 % to account for the contribution of the informal economy
$EGSI_{US_i}$	Estimated Gross State Income for each US state *(i)*; sum of the formal economy, informal economy and remittances as estimated from the nighttime lights image
$\mathrm{Residual}_{US_i}$	Residual Percentage for each U.S. state *(i)*, percentage difference between official $AGSP_{US_i}$ and modeled $EGSI_{US_i}$
A_{Ind_i}	Area of the lit urban areas for each Indian state and UT (*i*) demarcated by the brightness threshold
P'_{Ind_i}	Estimated 'U.S. equivalent urban population' for each Indian state and UT *(i)*
S_{Ind_i}	'Sum of lights' of the lit areas for each Indian state and UT *(i)*
GSP_{Ind_i}	Official Gross State Product of each Indian state and UT *(i)*
$EGSI_{Ind_i}$	Estimated Gross State Income for each Indian state and UT *(i)*: sum of the formal economy, informal economy and remittances, as estimated from the nighttime lights image
$EGDI_{Ind}$	Estimated Gross Domestic Income of India (sum of EGSI for all states and UTs)
$AEGDI_{Ind}$	$EGDI_{Ind}$ multiplied by "US_{URB} /Ind_{URB}" (ratio of percent urban population in the US to percent urban population in India) to derive Adjusted Estimated Gross Domestic Income of India
GNI_{Ind}	Official Gross National Income of India
$UIER$	Predicted underestimation of informal economy and remittances in the official estimates of GNI

Table 5: Official $AGSP_{US_i}$, Modeled $EGSI_{US_i}$, and Percentage Residuals for the U.S. states

U.S. States	Official $AGSP_{USi}$ (Mn $)*	$EGSI_{USi}$ (Mn $)	Percentage Residual
Alabama	126,034	195,001	-55
Arizona	174,386	147,181	16
Arkansas	73,481	112,061	-53
California	1,415,860	900,485	36
Colorado	189,048	147,449	22
Connecticut	176,480	116,503	34
Delaware	45,619	41,909	8
Florida	518,448	583,857	-13
Georgia	319,976	343,800	-7
Idaho	38,488	70,333	-83
Illinois	510,613	488,257	4
Indiana	213,861	263,892	-23
Iowa	99,205	176,838	-78
Kansas	91,093	111,667	-23
Kentucky	123,090	149,209	-21
Louisiana	144,672	182,660	-26
Maine	39,096	65,478	-67
Maryland	198,404	161,638	19
Massachusetts	302,444	170,528	44
Michigan	370,959	499,804	-35
Minnesota	203,602	290,706	-43
Mississippi	70,693	126,428	-79
Missouri	194,379	208,637	-7
Montana	23,503	64,156	-173
Nebraska	61,026	86,850	-42
Nevada	81,091	69,500	14
New Hampshire	47,870	67,358	-41
New Jersey	379,306	221,632	42
New Mexico	55,798	87,387	-57
New York	854,873	505,191	41
North Carolina	301,068	399,836	-33
North Dakota	19,527	59,650	-205
Ohio	409,207	560,518	-37
Oklahoma	98,733	148,215	-50
Oregon	123,682	88,137	29
Pennsylvania	428,581	579,311	-35
Rhode Island	36,970	33,301	10
South Carolina	123,765	205,450	-66
South Dakota	25,409	54,191	-113
Tennessee	192,336	236,374	-23
Texas	799,956	1,469,456	-84
Utah	74,325	89,223	-20
Vermont	19,560	35,674	-82
Virginia	286,817	226,155	21
Washington	244,157	157,625	35
West Virginia	45,624	90,620	-99
Wisconsin	193,311	342,603	-77
Wyoming	19,064	56,666	-197

* Source: U.S. Bureau of Economic Analysis

Table 6: Official GSP_{Ind_i} , Modeled $EGSI_{Ind_i}$, and Percentage Residuals for Indian states and Union Territories

States and Union Territories	Official GSP_{Indi} (PPP U.S. Mn $)*	EGSI $_{Indi}$ (PPP U.S. Mn $)	Residual %
Andaman and Nicobar Islands (UT)	1,069	2,447	-129
Andhra Pradesh	148,739	113,601	24
Assam	40,038	26,612	34
Bihar	96,951	37,202	62
Chandigarh (UT)	4,525	6,458	-43
Delhi	63,408	27,648	56
Gujarat	126,277	102,669	19
Haryana	58,940	64,420	-9
Himachal Pradesh	16,221	9,954	39
Jammu & Kashmir	18,000	12,651	30
Kerala	78,870	31,538	60
Madhya Pradesh	124,065	94,860	24
Maharashtra	284,433	185,718	35
Manipur	3,747	3,654	3
Meghalaya	4,181	3,211	23
Karnataka	110,608	84,065	24
Nagaland	3,218	2,496	22
Orissa	49,321	32,600	34
Pondicherry (UT)	3,718	8,498	-129
Punjab	77,214	76,958	0
Rajasthan	95,080	93,812	1
Tamil Nadu	154,238	113,507	26
Tripura	5,594	5,495	2
Uttar Pradesh	216,030	106,958	50
West Bengal	155,382	53,927	65
Arunachal Pradesh	1,857	2,543	-37
Mizoram	1,782	2,100	-18
Goa	7,276	13,003	-79

*Source: Central Statistical Organization, State Domestic Product – State Series

Table 7: Determining the magnitude of underestimation of informal economy and remittances in the official estimates of GNI of India

Row No.		In U.S. $ billions
1	Nighttime lights Estimated GDI of India ($EGDI_{Ind}$) (formal+informal+remittances)	1,319
2	Adjusted Estimated Gross Domestic Income ($AEGDI_{Ind}$) (multiplied by US_{URB}/Ind_{URB})	3,772
3	Official estimates of the GNI of India (GNI_{Ind}) (formal+informal+remittances) *	2,036
4	Predicted underestimation of remittances and informal economy ($UIER$)	1,736
5	Official estimates of Informal economy in 2000 ▲	1,115
6	Official estimates of remittances in 2000 #	13
7	Total official estimates of informal economy and remittances	1,128
8	Predicted underestimation of remittances and informal economy	1,736
9	Total official estimates of informal economy and remittances	1,128
10	Magnitude of underestimation	~ 150%

* Source: Central Statistical Organization, Summary of Macro Economic Aggregates at Current Prices, 1950-51 to 2008-09

▲ Source: Central Statistical Organization, National Accounts Statistics, 1980-81 to 1999-2000

\# Source: World Bank, 2000