ESTIMATING ECONOMIC ACTIVITY FROM SPACE

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Tilottama Ghosh

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Advisor: Dr. Paul Sutton

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ABSTRACT

Accurate estimates of the magnitude and spatial distribution of both formal and informal economic activity is necessary to achieve various social and economic goals of societies and countries at different levels of analysis. However, collection of data on economic variables, especially of national and sub-national income levels is problematic due to various shortcomings in the data collection process. Additionally, the informal economy estimates are often excluded from official statistics. Thus, developing alternative methods for estimating these economic activities may prove to be useful and necessary. This research demonstrates the potential of developing spatially explicit estimates of economic activity from nighttime satellite imagery as provided by the Defense Meteorological Satellite Program's Opertaional Linescan System (DMSP-OLS). The methods presented here are used to estimate formal and informal economic activity of Mexico and India at the sub-national level and to create a disaggregated global map of total economic activity. Regression models were developed between spatial patterns of nighttime imagery and Adjusted Official Gross State Product (*AGSP*) for the U.S. states. The regression parameters derived from the regression models of the U.S. were blindly applied to Mexico to estimate the Estimated Gross State Income (*EGSI*) at the sub-national level and the Estimated Gross Domestic Income (*EGDI*) at the national level. Comparison of the *EGDI* estimate of Mexico and official Gross National Income (*GNI*)

statistic demonstrated that the informal economy and inflow of remittances for Mexico was about 50 percent larger than what was recorded in the official *GNI* statistic. However, when the regression parameters were applied to India, Gross State Income (*GSI*) was underestimated for most of the states and Union Territories (UTs) of India in comparison to their official *GSP*, although it provided a high correlation (r = 0.93) between them. This was probably because of the lower level of urbanization in India in comparison to the U.S. To adjust for the different levels of urbanization in the U.S. and India, the *EGDI* was multiplied by the ratio of the percentage of the population in urban areas for the two countries. Comparing the Adjusted Estimated Gross Domestic Income (*AEGDI*) with the official *GNI* statistic of India suggested that the magnitude of India's informal economy and the inflow of remittances may also be 50 percent larger than what was recorded in the official *GNI* value. Lastly, a global disaggregated map of total (formal plus informal) economic activity was created. This was done by multiplying the sum of light intensity values of the administrative units (states of China, India, Mexico, and the U.S., and other countries of the world) with computed unique coefficients. This provided estimated total economic activity ($GSPI_i$ and $GDPI_i$) for each administrative unit. The total economic activity values were spatially distributed (disaggregated) within each administrative unit using the percentage contribution of agriculture towards *GDP* for each country, combined with raster representations of the nighttime lights image and the LandScan population grid. This generated a spatially disaggregated 30 arc-second or one km^2 map of estimated total economic activity.

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CHAPTER 1

INTRODUCTION

This research presents an attempt to estimate and map the distribution of economic activity at the sub-national, national, and global level based on nighttime lights imagery, official statistics of economic activity, estimates of informal economic activity, and the LandScan population grid. Image analysis techniques and Geographic Information Systems (GIS) applications were used extensively to estimate economic activity. A look at the nighttime lights imagery (figure 1.1) shows how conspicuous the relationship between economic activity and nighttime lights is – the brightly lit areas are the richer countries of the world (e.g., the United States and Western European countries), and the areas with deficiency in lighting are the poorer countries of the world (e.g., African countries).
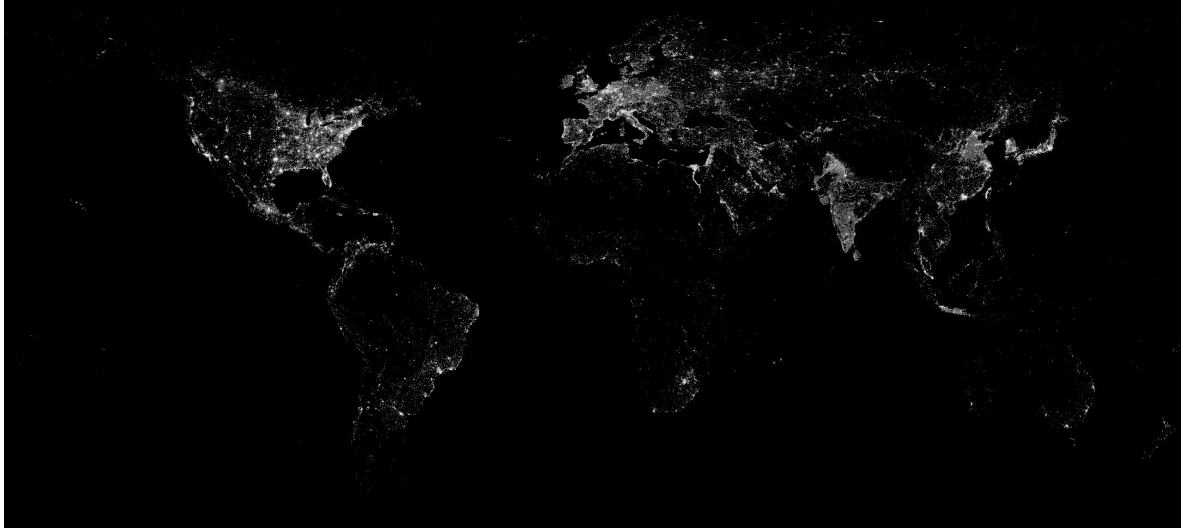
Figure 1.1: Nighttime lights imagery of 2006.

Economic activity can be categorized into formal and informal activities. Formal economic activities are usually registered with the government, are subject to taxation, and are included in official economic censuses. Informal economic activities (also referred to as shadow economies), on the other hand, include market-based legal production of goods and services that are intentionally concealed from public authorities – to avoid payment of taxes and social security contributions, to avoid certain legal labor market standards such as, minimum wages, maximum working hours, safety standards, etc., and to avoid fulfilling certain administrative procedures, such as statistical questionnaires (Buehn and Schneider 2009). This research represents a deliberate effort to estimate both formal and informal economic activity using nighttime lights.

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This research links geography with economics as it studies the spatial distribution of economic activity (Arnott and Wrigley 2001). It focuses on the efficiency and equitability of the distribution of wealth. This inquiry fits into the broader domain of economic geography. Following the brief introductory chapter, the second chapter includes definitions and measures of the formal and informal economy and causes for the rise of informal economic activity. The third chapter discusses problems associated with measuring and mapping of formal and informal economic activity; the need to develop proxy measures of economic activity; the importance of the nighttime lights as a proxy measure of economic activity with descriptions of different types of nighttime lights imagery; and, studies of economic activity that have been done using nighttime imagery. The fourth chapter attempts an independent estimation of Mexico's informal economy and remittances from nighttime imagery based on parameters derived from the spatial patterns of nighttime satellite imagery and economic activity in the United States (U.S.). The fifth chapter deals with a similar attempt at estimating the informal economy and remittances of India based on the U.S. parameters. A disaggregated global map of total (formal plus informal) economic activity is produced in chapter six. Chapter seven discusses the various implications and applications of this research, analysis of the drawbacks and benefits of the use of nighttime imagery as a proxy measure and avenues for future research.

CHAPTER 2

THE INFORMAL AND FORMAL ECONOMY

2.1 What is the informal economy?

The informal economy is present in both developing and developed countries. Visible manifestations of the informal economy exist in the streets of cities, towns, and villages lined with barbers, cobblers, garbage collectors, and vendors selling an increasingly diverse array of products including vegetables, fruits, dead fish, live chickens, cell phone batteries, and cigarettes. In many developing countries, like India, it is all too common to see cart pullers, bicycle peddlers, rickshaw pullers, bullock and horse cart drivers, compete with the cars, buses, scooters, and motorcycles to make their way through the narrow and wide streets (Chen 2003). Less visible manifestations of this process are the informal workers who work in small shops or workshops; for example, 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 (International Labor Organization, ILO 2002). All these workers engaged in the informal economy are employed without any secure contracts, worker benefits or social protection.

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2.2 Defining informal economy –

Recognizing the importance of the informal economy and the need to gather statistics related to informal economy, the Fifteenth International Conference of Labor Statisticians (15th ICLS) in January, 1993 adopted the international statistical definition of the informal sector or informal enterprises. This was subsequently included in the revised International System of National Accounts (SNA 1993). The definition adopted in the 15th ICLS is as follows:

"The informal sector is regarded as a group of household enterprises or unincorporated enterprises owned by households that includes:

- Informal own-account enterprises, which may employ contributing family workers and employees on an occasional basis; and
- Enterprises of informal employers – owned and operated by employers, either alone or in partnership with members of same or other households, but which employ one or more employees on a continual basis. The enterprise of informal employers must fulfill one or both of the following criteria: size of the unit must be below a specified level of employment, and non-registration of the enterprise or its employees (labor laws)."

Given this definition, flexibility is allowed with regards to the upper limit or the size of employment; the introduction of additional criteria such as non-registration of either the enterprise or its employees; the inclusion or exclusion of employees; the inclusion or exclusion of agriculture (ILO 2002).

This definition was based on the characteristics of production units/enterprises (enterprise approach) rather than characteristics of persons or their jobs (labor approach). From the time of the adoption of the definition of the informal sector in the 15th ICLS, a group of informed activists and researchers, including the Expert Group on Informal

Sector Statistics (Delhi Group), Women in Informal Employment Globalizing and Organizing (WIEGO), and the Bureau of Statistics, International Labor Office (ILO), realized the need to broaden the concept and definition of the informal sector by including not only enterprises that are not regulated, but also employment relationships that are not legally regulated or protected. Thus, the broader definition of informal economy which was adopted in the 17th ICLS in 2003 includes both the unregulated nature of employment and the characteristics of enterprises to describe informal economy (Chen 2007). Thus, under the new definition, the informal economy or informal employment is comprised of:

- "Self-employment in informal enterprises: self-employed persons in small unregistered or unincorporated enterprises, including – employers, own account operators, unpaid contributing family workers.
- Wage employment in informal jobs: wage workers without legal protection for formal or informal firms, for contractors, for households, or with no fixed employer, including – non-standard employees of informal enterprises, non-standard employees of formal enterprises, casual or day laborers, industrial outworkers (also called homeworkers)."

Thus, the conceptual framework of informal employment (figure 2.1) as adopted in the 17th ICLS disaggregates the total employment according to two dimensions: type of production unit and type of job. Type of production unit (rows of the matrix) is defined in terms of legal organization and other enterprise related characteristics, while type of job (columns of the matrix) is defined in terms of status in employment and other job-related characteristics (Hussmanns 2004).

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A Conceptual Framework: The Informal Economy									
Production units by type	Jobs by status in employment								
	Own-account workers		Employers		Contributing family workers	Employees		Members of producers' cooperatives	
	Informal	Formal	Informal	Formal	Informal	Informal	Formal	Informal	Formal
Formal sector enterprises					1	2			
Informal sector enterprises [a]	3		4		5	6	7	8	
Households [b]	9					10			

[a] As defined by the Fifteenth International Conference of Labour Statisticians in 1993 (see box on 1993 ICLS definition of informal sector)
[b] Households producing goods for their own final use and households employing domestic workers.

Figure 2.1: Conceptual framework of the informal economy (Source: ILO 2002).

Employment in the informal sector – Sum of cells 3 to 8

Informal employment or totality of informal economy– Sum of cells 1 to 6 and 8 to 10

Informal employment outside the informal sector – Sum of cells 1, 2, 9, and 10

Employees working in the informal enterprises but having formal jobs (This may occur, for example, when enterprises are defined as informal using size as the only criterion) – Cell 7

The common underlying factor for all workers who are employed informally is the lack of secure work, worker's benefits, social protection and representation of voice. The self-employed have the sole responsibility to take care of themselves and their enterprises. The informal workers are also at a competitive disadvantage in relation to

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larger formal firms in both the capital and product markets. As a result of these factors, a high percentage of people working in the informal economy as compared to those in the formal economy are poor (ILO 2002).

2.3 Causes for the rise of informal economy –

There was considerable speculation for a long period of time regarding the permanence of the informal economy in the global context. Economists believed that with the growth of the modern capitalist economy, the informal workers and producers would be engulfed into the broad capitalist economy. However, by the 1980s it was realized that the informal, traditional economy was here to stay, as a permanent and integral part of the global capitalist economy (ILO 2002).

Changes in the patterns of production in the biggest capitalist economies, North America and Europe, in the 1980s confirmed the permanence of the informal economy. Mass production was reorganized into small scale, decentralized and flexible units of production. This change in the structure of production resulted in the 'informalization' of employment relations – standard jobs were replaced with non-standard or atypical jobs with hourly wages and few benefits, or into piece-rate jobs with no benefits. The production of goods and services were also subcontracted to small scale informal units and industrial outworkers. The changes brought about in the 1980s continue to be a feature of the modern capitalist economy (Portes et al. 1989; Chen 2003).

The economic downturn in Latin America in the 1980s highlighted another feature of the informal economy – its tendency to grow and expand during periods of economic crisis (Tokman 1992). Similar expansion of the workforce in the informal economy was

noticed during the Asian economic recession about a decade or more later and during the periods of structural adjustment in Africa and economic transition in the former Soviet Union and in Central and Eastern Europe. During times of economic recession, when private firms or public enterprises are downsized or closed, workers who are laid off seek refuge in the informal economy. Moreover, because of the inflationary prices or curtailment of public services during the bad economic times, households often have to work in the informal economy to supplement their meager earnings in the formal economy (Chen 2003). The global economic recession, which started in September of 2008 is causing more people to join the informal workforce (United Nations 2009).

Globalization of the economy beginning in the 1990s also contributes to the 'informalization' of the workforce in many industries and countries. Global competitive forces often result in firms making an effort to cut down their costs. In order to achieve this, they hire workers at low wages with little benefits or sub-contract or even outsource the production of goods and services. Besides, globalization affects the informal units themselves. Many domestic informal units or self-employed producers often fail to withstand the competition with the imported goods which flow into the domestic market as a result of global integration. They also cannot compete with the superior products made by formal firms for the export markets (Rodrik 1997; 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). The urban poor often

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live in deplorable conditions in the slums without access to waste disposal, water supplies, proper sanitation, food supplies and housing. Dharavi, in India, is one of the largest slums in Mumbai and it houses up to 10,000 small factories, which provide an income to approximately 1 million people and yields an estimated $665 million in annual revenue (Delgado 2008).

Friedrich Schneider, of the Johannes Kepler University at Linz, Austria, in developing the DYMIMIC (dynamic multiple-indicators multiple-causes) model for estimating informal economy of the countries of the world analyzed the causes of the rise and persistence of the informal economy. He summarized three main causes to be chiefly responsible for contributing towards the informal (shadow) economy (Schneider 2007):

(i) The burden of direct and indirect taxation, both actual and perceived. There exists a positive correlation between a rising burden of taxation and a strong motivation to work in the informal economy.

(ii) Excessive government intervention in civil society and economic activities also causes more workers to enter the informal economy as it often creates "hyper-bureaucratization." This deters citizens from pursuing the legal path. Thus, increases in the burden of regulation provide a strong incentive to the workers to enter informal economy.

(iii) The "tax morality", i.e., the citizens' attitudes toward the state, which indicates the willingness of individuals to leave their official occupations in order to enter the informal economy. Declining tax morality is positively correlated with the increase in the size of the informal economy.

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2.4 Statistics on informal employment –

Few countries measure employment in informal enterprises and even fewer countries measure informal employment outside informal enterprises. In the absence of direct methods, indirect methods have been developed to estimate informal employment. Only five countries, (Tunisia, South Africa, Mexico, Kenya, and India) have conducted direct informal sector or mixed surveys and have employed indirect methods to estimate informal employment outside the informal enterprises. Thus, through a combination of direct and indirect methods these five countries have estimated the total informal employment (ILO 2002). For other countries, indirect method, known as the "residual method" is employed to estimate economic activity based on existing published data, for example, tabulations based on population census, labor force survey, or household surveys that cross-classify industrial sectors (i.e, agriculture, mining, manufacturing, trade and services, by employment status (i.e., employers, own-account workers, family workers, employees) and by sex (ILO 2002). Table 2.1 shows informal employment as percentage of non-agricultural employment for selected regions and countries. For the data available for the years 1994/2000, informal employment as percentage of non-agricultural employment varied between 48 percent in North Africa to 65 percent in Asia. However, there was considerable variation within the regions. For example, within Asia, informal employment as percentage of non-agricultural employment varied between 42 percent in Syria and 83 percent in India.

Table 2.1 Informal employment as percentage of non-agricultural employment for selected regions and countries, 1994/2000

Region/country	Informal employment as percentage of non-agricultural employment
North Africa	**48**
Algeria	43
Morocco	45
Tunisia	50
Egypt	55
Sub-Saharan Africa	**72**
Benin	93
Chad	74
Guinea	72
Kenya	72
South Africa	51
Latin America	**51**
Bolivia	63
Brazil	60
Chile	36
Colombia	38
Costa Rica	44
El Salvador	57
Guatemala	56
Honduras	58
Mexico	55
Rep Dominicana	48
Venezuela	47
Asia	**65**
India	83
Indonesia	78
Philippines	72
Thailand	51
Syria	42

Source: ILO 2002, Data prepared by Jacques Charmes

Only three countries – India, Mexico and South Africa have distinguished between formal and informal activities in agriculture and have included informal agriculture as a distinct category in estimates of informal economy. The inclusion of informal employment in agriculture increases significantly the proportion of informal

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employment: from 83 percent of non-agricultural employment to 93 percent of total employment in India; and from 55 percent to 62 percent in Mexico. Three categories of non-standard or atypical work – part time work, temporary work and self-employment comprise 30 percent of overall employment in 15 European countries and 25 percent of total employment in the U.S. (ILO 2002).

2.5 Statistics on the contribution of informal sector towards Gross Domestic Product (*GDP*) -

According to the International Labor Organization (ILO) statistical report of 2002, there are as such no estimates of the contribution of the informal economy (that is, contribution of informal enterprises plus contribution of people who are employed informally outside the informal enterprises) as a whole towards *GDP*. Nevertheless, there are estimates of contribution of just the informal enterprises towards *GDP*. Table 2.2 shows the contribution of informal sector to *GDP* in selected developing countries for years ranging between 1979 and 1998. It varied from 27 percent in Northern Africa to 41 percent in Sub-Saharan Africa, to 29 percent in Latin America, and 31 percent in Asia. There was also great variation in the contribution of the informal sector *GDP* as percentage of non-agricultural *GDP* within the countries, as for the three countries of Latin America which are listed it is seen that it varied between 13 percent in Mexico to 49 percent in Peru.

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Table 2.2 Contribution of informal sector to *GDP* in selected developing countries

Country (year)	Informal sector GDP as percentage of non-agricultural GDP
Africa	
Northern Africa	**27**
Algeria (1997)	26
Morocco (1986)	31
Tunisia (1995)	23
Sub-Saharan Africa	**41**
Benin (1993)	43
Burkina Faso (1992)	36
Burundi (1996)	44
Cameroon (1995-96)	42
Chad (1993)	45
Côte d'Ivoire (1995)	30
Ghana (1988)	58
Guinea Bissau (1995)	30
Kenya (1999)	25
Mali (1989)	42
Mozambique (1994)	39
Niger (1995)	54
Senegal (1991)	41
Tanzania (1991)	43
Togo (1995)	55
Zambia (1998)	24
Latin America	**29**
Colombia (1992)	25
Mexico (1998)	13
Peru (1979)	49
Asia	**31**
India (1990-91)	45
Indonesia (1998)	31
Philippines (1995)	32
Republic of Korea (1995)	17

Source: ILO 2002, Data prepared by Jacques Charmes

2.6 Methods for estimating contribution of informal economy towards *GDP* -

Measuring the size of the informal economy in a country's national economy is a challenging task. There exist some direct and indirect approaches to measure the size of the informal economy of a country (Schneider and Enste 2000).

2.6.1 Direct approaches -

The two main direct approaches for estimating the informal economy of a country are sample surveys and tax auditing. Sample survey is a common method which is used in a number of countries. The main disadvantage of this method is that the accuracy of the data collected through these surveys depends to a great extent on the willingness of the responders to cooperate and divulge their 'undeclared' work. However, if the questionnaires are formulated intelligently, then a lot of detailed information may be gathered through these surveys.

Estimates of informal economy can also be made based on the inconsistency between declared incomes for tax purposes and that measured by selective checks like fiscal auditing programs. As the fiscal auditing programs have been designed to measure the amount of undeclared taxable income, they have been used in several countries to calculate the informal economy. The main disadvantage of this method is that the data collected for the tax payers for tax audit represent a section of the population who has committed some kind of tax fraud and does not represent the whole population. So, the

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sample may be biased in this case and may represent only that portion of the black money income which the authorities were successful in discovering.

2.6.2 Indirect approaches -

The most common indirect approaches for estimating the size of the informal economy are – The Currency Demand Approach, the Electricity Consumption or Physical Input Method, and The Model Approach.

(i) The Currency Demand Approach -

The Currency Demand Approach presumes that transactions in the informal economy are mostly undertaken in the form of cash payments. Thus, an increase of demand for currency would indicate an increase in informal economy. A regression equation of currency demand is developed econometrically by taking into account factors such as weighted average tax rate (to proxy changes in the size of the informal economy); proportion of wages and salaries in national income (to capture changing payment and money holding patterns); the interest paid on savings deposits (to capture the opportunity cost of holding cash); and per capita income. The excessive increase in currency, the amount which could not be explained by the conventional factors mentioned above, is attributed to the rising tax burden which motivates people to work in the informal economy. The Currency Demand Approach is one of the most commonly used indirect methods for estimating informal economy. The main criticisms of this method are –

a) This method may be underestimating the size of the informal economy as not all transactions in the informal economy are paid in cash.

b) Tax burden is not the only factor causing an increase in informal economy. There may be other factors, such as, the impact of regulation, taxpayers' attitude towards the state, "tax morality" of the tax payers and so on. These factors are often not taken into consideration, as reliable data of these factors are not available. Thus, it can be rightly assumed that not taking these factors into consideration leads to an underestimation of informal economy.

(ii) The Physical Input or Electricity Consumption Method:

The Kaufmann- Kaliberda Method

Kaufmann and Kaliberda (1996) consider electricity consumption to be the single best physical indicator of overall economic activity. They derived an overall estimate of unofficial *GDP* by subtracting official measures of *GDP* from a proxy measurement of overall economy derived from electricity consumption. The difference between growth of electricity consumption and growth of official *GDP* is used as a proxy for the growth of the informal economy. Although this method is simple and appealing, it has been subjected to criticism because -

a) Not all informal economic activity, like personal services require a considerable amount of electricity and other energy sources, such as gas, coal, oil, etc. may also be used, and thus this method may actually capture only a part of the informal economy.

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b) Although official/unofficial economic activity and electricity consumption have been empirically observed to be very closely related, the relationship may vary across countries or may also change over time.

The Lacko Method

According to Lacko (1998, 2000), a certain part of the informal economy is associated with the household consumption of electricity, including so-called household production and other non-registered production and services. Thus, in countries where the part of the informal economy associated with household electricity consumption is high, the rest of the hidden economy that cannot be measured is also high. However, Lacko's method has also been criticized because:

a) It is argued that not all informal economic activities require a considerable amount of electricity and other energy sources can be used

b) Also, informal economic activities do not take place only in the household sector.

(iii) The Model Approach

The pioneers of this approach were Weck (1983), Frey and Weck (1983a, 1983b), Frey and Weck-Hanneman (1984). The two previous methods described for estimating the size and contribution of the informal economy consider just one indicator of the effects of informal economy, that is, the increased flow of cash, in the case of currency demand approach, and increased consumption of electricity in the case of electricity

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consumption method. The monetary approaches also consider only one cause, that is, the burden of taxation as the cause of increase in informal economic activity.

The model approach (MIMIC model, the Multiple Causes and Multiple Indicators model) considers multiple causes as well as multiple effects of the informal economy. This empirical method is based on the statistical theory of unobserved variables, which consider multiple causes and multiple indicators of the phenomenon. The hidden economy is estimated as an unobserved variable over time through a factor-analytic approach. The DYMIMIC (dynamic multiple-indicators multiple-causes) model consists in general of two parts – the measurement model and the structural equations model. The measurement model links the unobserved variables to observed indicators and the structural equations model specifies causal relationships among the unobserved variables. The unobserved variable in this case is the size of the informal economy. It is assumed to be influenced by a set of indicators for the informal economy's size, thus portraying the structural dependence of the informal economy on variables that may be useful in predicting its movement and size in the future. The interaction over time between the causes Z_{it} (i =1, 2, ….,k), the size of the informal economy X_t, and the indicators Y_{jt} (j = 1, 2, …., p) is shown in figure 2.2. The three main causes giving rise to informal economy are - high taxation, heavy regulation, and declining "tax morality". The indicators of informal economy are – monetary indicators – if activities in the informal economy rise, additional monetary transactions are required; labor market indicators – increased participation of workers in the hidden sector would result in decreased participation in the official economy; and lastly, production market indicators - when there is an increase of

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informal economy activity, inputs (especially labor) move out from the official economy and this displacement can have an overall depressing effect on the official growth of the economy (Schneider 2002).

Figure 2.2: The DYMIMIC model: Development of the informal economy over time.
Source: Schneider and Enste 2000
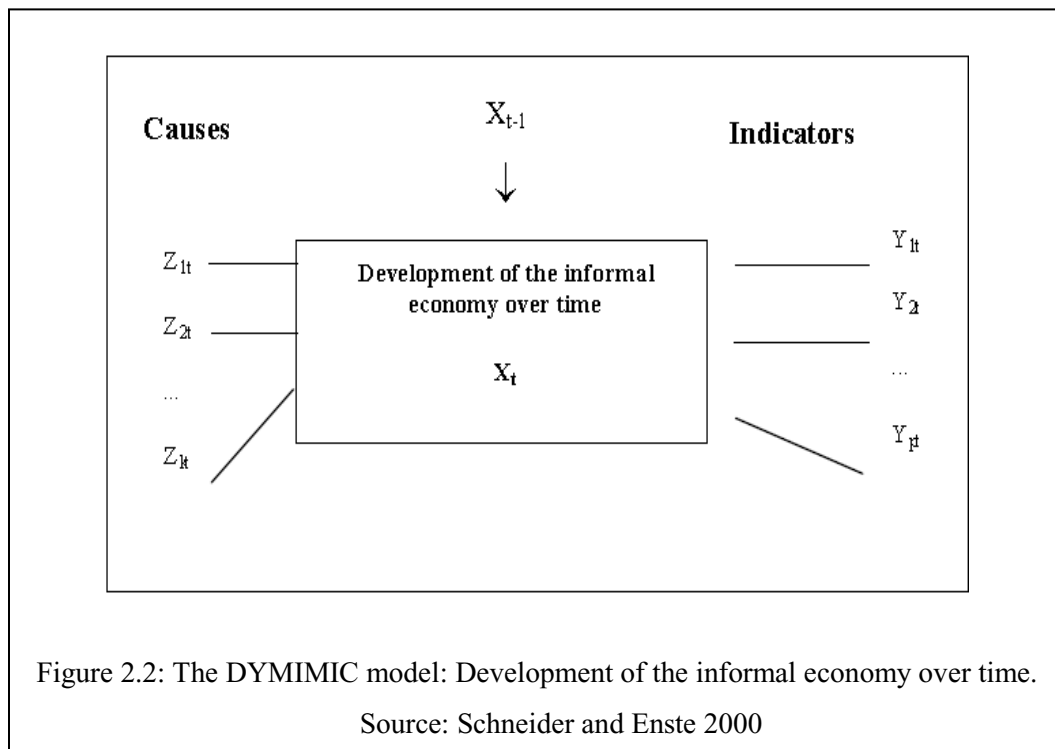
The DYMIMIC model is different among all the common methods for estimating informal economy because it considers multiple causes leading to the existence and growth of informal economy, as well as multiple effects of the informal economy over time. Friedrich Schneider estimated the average informal economy (which he calls shadow economy) for 96 developing countries, 25 transition economies, and 21 Organization for Economic Co-operation and Development (OECD) countries, to be 36.7

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percent, 38.8 percent, and 14.8 percent, respectively using the DYMIMIC model (Schneider 2007). These estimates have been used in creating the disaggregated map of economic activity in chapter six. The direct tax (and social security) payment and indirect tax (and customs tariff) burden variables are the driving forces for the growth of the informal economy for all the three types of countries. The tax burden is followed by the measure of state (labor market) regulation, and, as measures of the official economy, the unemployment quota and *GDP* per capita, are the other important driving forces. The relative importance of the causative factors however varies in the three types of countries. For the developing countries, the burden of state regulation, followed by the unemployment quota and the share of indirect taxation have the greatest influence. In the transition countries direct taxation (including social security payments) has the greatest influence, followed by the unemployment quota and the share of indirect taxation. In the highly developed OECD countries, the greatest influence is exercised by the social security contributions and the share of direct taxation, followed by tax morale and the quality of state institutions (Schneider 2007).

2.7 The formal economy – the continuum between formal and informal Economy -

Formal economies of countries are registered with the government, pay taxes and are included in the official censuses. There is no absolute division between formal and informal economy. In fact, the economic relations pertaining to production, distribution, and employment fall at some point on a continuum between pure formal (i.e., regulated and protected) at one end and pure informal (i.e., unregulated and unprotected) at the

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other, with many categories in between. Workers and units move along the continuum depending on their conditions and needs and may even operate simultaneously in both the sectors. For example, a self-employed tailor may supplement her earnings by making garments for a firm under a sub-contract, or a public sector employee may also be engaged in an informal job. Thus, the formal and informal sectors are often dynamically linked. Informal enterprises are often involved in supplying inputs, finished goods or services to the formal enterprises, either through direct transactions or under sub-contraction. Again, many formal enterprises also hire wage workers (part-time workers, temporary workers, and homeworkers) through contractual or sub-contractual arrangements (Chen 2007).

2.8 Official measures of the formal economy –

(i) Gross Domestic Product (*GDP*) - *GDP* is the market value of all final goods and services produced in a given country in a given year, equal to total consumer, investment, and government spending, plus the value of exports, minus the value of imports (Sullivan and Sheffrin 1996). *GDP* helps to measure the economic growth of a country. *GDP* at the state or sub-national level is referred to as Gross State Product (*GSP*).

(ii) Gross National Income (*GNI*) - The most common index for measuring a nation's income is the gross national income (*GNI*, the term now preferred by World Bank). This is also known as the Gross National Product (*GNP*). The World Bank defines *GNI* (formerly *GNP*) as the –

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"The value of all final goods and services produced in a country in one year (gross domestic product) plus income that residents have received from abroad, minus income claimed by nonresidents." (World Bank, DEPweb).

Thus, *GNI* is the value of all paid work that goes on within the boundaries of a country with the addition of money received from other countries. If the money received from abroad is excluded and the income generated only within the country's boundary is considered, it is the *GDP* (Weeks 2005).

For making international comparisons possible, *GDP* and *GNI* data are often expressed in Purchasing Power Parity (PPP) U.S. dollars. Purchasing power parity 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). This concept can be explained through the use of what *The Economist* calls its "Big Mac Index." McDonald's sells its hamburgers in nearly 120 countries, and in every country, the sandwich must confirm to some specific standard of ingredients and preparation. If the Big Mac costs $2.71 in the United States, then it should cost the same in real terms anywhere else in the world. So if you pay 1,400 pesos for a Big Mac in Chile, then you are paying 1,400/2.7 = 516.6 Chilean Pesos per U.S. dollar, in terms of the "real" cost of living (Ong 2003). By applying the PPP conversion factor, a country's nominal *GNI* or *GDP* (expressed in U.S. dollars in accordance with the market exchange rate of the national currency) is converted into its real *GNI* or *GDP* (an indicator adjusted for the difference in prices for the same goods and services between the country and the U.S., and independent of the fluctuations of the national

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currency exchange rate). *GNI* and *GDP* in PPP terms thus provide a better comparison of average income or consumption between economies (Sheram and Soubbotina 2000).

(iii) Remittances - Remittances are the funds that international migrants send back to their countries of origin and thus remittances contribute to the *GNI* of a country. These funds have emerged as a major source of external financing in developing countries in recent years. Workers' remittances, compensation of employees and migrant transfers are considered to be the officially recorded flows on the basis of which the remittances are estimated. Because of increased flow of remittances and their potential to reduce poverty, remittances have been receiving increased attention from policymakers at the highest levels in both developed and developing countries (World Bank 2006).

Workers' remittances, are current private transfers from migrant workers who are considered residents of the host country to recipients in the country of origin. If a migrant lives in a host country for a year or longer he is considered to be a resident of that country, regardless of his immigration status. If he has lived in the country for less than a year, the entire income in the host country should be considered as compensation of employees. Workers' remittances are considered to be transfers, while compensation of employees is considered factor income (World Bank 2006). Migrants' transfers are small in comparison to workers' remittances and compensation of employees. Migrants' transfers arise when individuals move their residence from one economy to another. They include the movement of financial assets between countries and changes in stock position of personal investments and debt arising from the change in residence status (Reinke

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2005). For example, if a migrant moves from France to Germany, the value of IBM stock owned by him gets transferred in international accounting. At present migrant transfers are considered as capital transfers in Balance of Payments (BoP).

Most estimates of remittances are based on BoP statistics reported to the International Monetary Fund (IMF) by the Central Banks of the recipient countries. The numbers on the BoP are generally considered to be an underestimate of actual remittances as they include only the officially recorded flows in BoP data reported by the remittance-receiving countries.

CHAPTER 3

PROBLEMS OF ESTIMATION AND MAPPING OF FORMAL AND INFORMAL ECONOMY AND DEVELOPMENT OF PROXY MEASURES

There are several problems associated with the estimation and mapping of the formal and informal economies of countries. This chapter discusses the problems, the need to develop proxy measures, and the importance of nighttime lights imagery as a proxy measure of economic activity.

3.1 Problems of estimating informal economy and contribution of informal economy towards *GDP* -

The brief discussions about the existing estimates of informal employment and contributions of informal economy towards *GDP* in the previous chapter highlights the great amount of uncertainties and discrepancies that exist in all estimates of informal economy. Through a mixture of different direct and indirect methods, different estimates of the population engaged in informal economy or the contributions of informal economy towards *GDP* are derived. To reiterate, gathering statistics on the size, composition and contribution of the informal economy is an extremely complicated exercise. The primary limitation is that very few countries have undertaken regular surveys on the informal sector and only two or three countries have collected data that provide for measures

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of informal employment outside informal enterprises. Again, very few countries have prepared estimates of the contribution of the informal sector to *GDP*.

Furthermore, the available official data are not all-inclusive. Some countries measure only the urban informal sector and agriculture is excluded. In addition, there is no uniformity and standardization in the presentation of the data. As a result, it often leads to faulty comparison. For example, informal sector will be underestimated if data on the informal sector (excluding agriculture) are compared to data on the total workforce (including agriculture) (ILO 2002).

3.2 Problems of estimating the formal economy – Gross Domestic Product (*GDP*), Gross State Product (*GSP*) and remittances

There are several challenges to the collection of high quality *GDP* and *GSP* data, including the absence of standardized national income accounting methods, different bureaucratic capacity of states, lack of consistent methodology in data collection, low levels of efficiency of surveyors, the subjective response of the responders in ground surveys, and the political and economic situation of countries (Min 2008; Henderson et al. 2009). Poor countries, having a weaker government infrastructure than developed countries, are most likely to have the most imprecise and unreliable estimates. Again, it is practically impossible to collect reliable economic data in a country ravaged by war. More importantly, in many developing countries, a greater percentage of economic activity is conducted within the informal sector than the formal sectors, and informal

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sector productivity is often excluded from the formal statistics (Ebener et al. 2005; Sutton et al. 2007; Ghosh et al. 2009; Henderson et al. 2009).

Some countries do not even have national accounts data. For example, Iraq, Myanmar, Somalia, and Liberia, are countries which were not included in the most recent version of the Penn World Tables 6.2 (PWT). The PWT are, purchasing power parity and national income accounts converted to international prices for 188 countries for some or all of the years between 1950-2004 provided by the Center for International Comparisons at the University of Pennsylvania (Henderson et al. 2009). For most developing countries, and even for a few developed countries, reliable economic data on output at the sub-national level, particularly for cities and even larger regions, are often not available (Henderson et al. 2009).

Measurement errors of formal economic activity may also arise because of the different purchasing power parity values used, different computation methodologies, revisions in the underlying national income account data, or basic human error during tabulation of data. An example of measurement error is given by Johnston et al. (2009) in their study of the revisions of the PWT. The authors calculated the ten worst growth performers in Africa based on the version 6.1 data released in 2002 and version 6.2 data released in 2006. Only five countries were present in both lists. Johnston et al. (2009) concluded from their analysis that since these two versions of data used the same purchasing power parity values, the discrepancy which was observed was due to revisions in the national income accounts data used. Another classic example of a statistical glitch by the World Bank economists is from the *New York Times* article

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published on December 9, 2007 (Porter 2007). The economists had measured the Chinese economy to be four trillion dollars more than what it really was. The revised estimate of the size of the Chinese economy was six trillion dollars instead of ten trillion dollars as was previously estimated. They attributed this mistake to the use of older Chinese prices from 1980 to develop the purchasing power parity estimates. Again, in a recent article in *The Economist*, China's *GDP* of 2008 was stated to be $ 4.4 trillion (Miles 2009). The different values of *GDP* gathered from different official sources bring into question the reliability of official data.

Most measures of remittances are based on Balance of Payments (BoP) statistics reported to the International Monetary Fund (IMF) by the Central Banks of the recipient countries. The numbers on the BoP are generally considered to be an underestimate of actual remittances, as they include only the officially recorded flows in BoP data. 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 classified as export revenue, tourism receipts, nonresident deposits, or even foreign direct investment (FDI) (World Bank 2006).

3.3 Problems associated with mapping of economic activity –

Maps of the global distribution of national income are usually available on a national basis, as it is a convenient administrative unit for data collection. However, this prevents the integration of socio-economic and physical and environmental data (e.g., global land

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cover/land use, elevation data, climate, soil, and vegetation data), which are available in raster or grid formats (i.e., a matrix of cells or pixels organized in rows or columns). Therefore, it is necessary to develop disaggregated maps (i.e., maps in raster or grid formats) of economic activity.

3.4 The need for better economic estimates –

In the United Nations Millennium Summit of September 2000, the Millennium Development Goals (MDGs), a list of eight goals and eighteen targets were adopted by 189 nations. They set some quantitative benchmarks to halve extreme poverty in all its forms and a target date of 2015 was set to achieve these goals.

The eight MDGs are:

> Goal 1: Eradicate extreme poverty and hunger
> Goal 2: Achieve universal primary education
> Goal 3: Promote gender equality and empower women
> Goal 4: Reduce child mortality
> Goal 5: Improve maternal health
> Goal 6: Combat HIV/AIDS, malaria and other diseases
> Goal 7: Ensure environmental sustainability
> Goal 8: Develop a Global Partnership for Development

The global economic crisis has proved to be a major setback towards the achievement of the MDGs. It has worsened the economic situation of countries by pushing more people into poverty and forcing tens of millions of people into vulnerable informal employment (United Nations 2009). Understanding the global distribution of wealth and how it affects the economic well-being of the population assumes immense importance in the context of achieving the MDGs and for implementing various policy decisions (Sachs 2005).

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Although not many reliable statistics are available for informal economy, the few that are available show that informal workers comprise a substantial proportion of the employed workforce in both the developed and developing countries and their numbers are much larger than most people realize them to be. They also contribute a significant proportion towards *GDP*. Because of the importance of the informal economy in a country's total economy, the economic performance of a country can only be modeled or predicted if the value of the informal economy in the total output of the country is adequately measured or valued. Again, labor market behavior can be predicted and modeled adequately only if the major segment of the total workforce, that is, the informal economy workforce is adequately measured and understood (ILO 2002).

Although there is no direct link between working in the informal economy and being poor, the fact that workers and enterprises in the informal economy receive no legal protection or worker benefits and are often at a competitive disadvantage in relation to larger formal firms in both the capital and product markets, a significant overlap is observed between working in the informal economy and being poor. This relationship between the informal economy and low income becomes conspicuous only when informal work is analyzed by economic sub-sectors and by status of employment (employer, own-account worker, wage worker). The linkages can best be depicted through the 'pyramid' or 'iceberg' figure (figure 3.1).

Figure 3.1: Informality, poverty and gender.

Source: Chen 2007
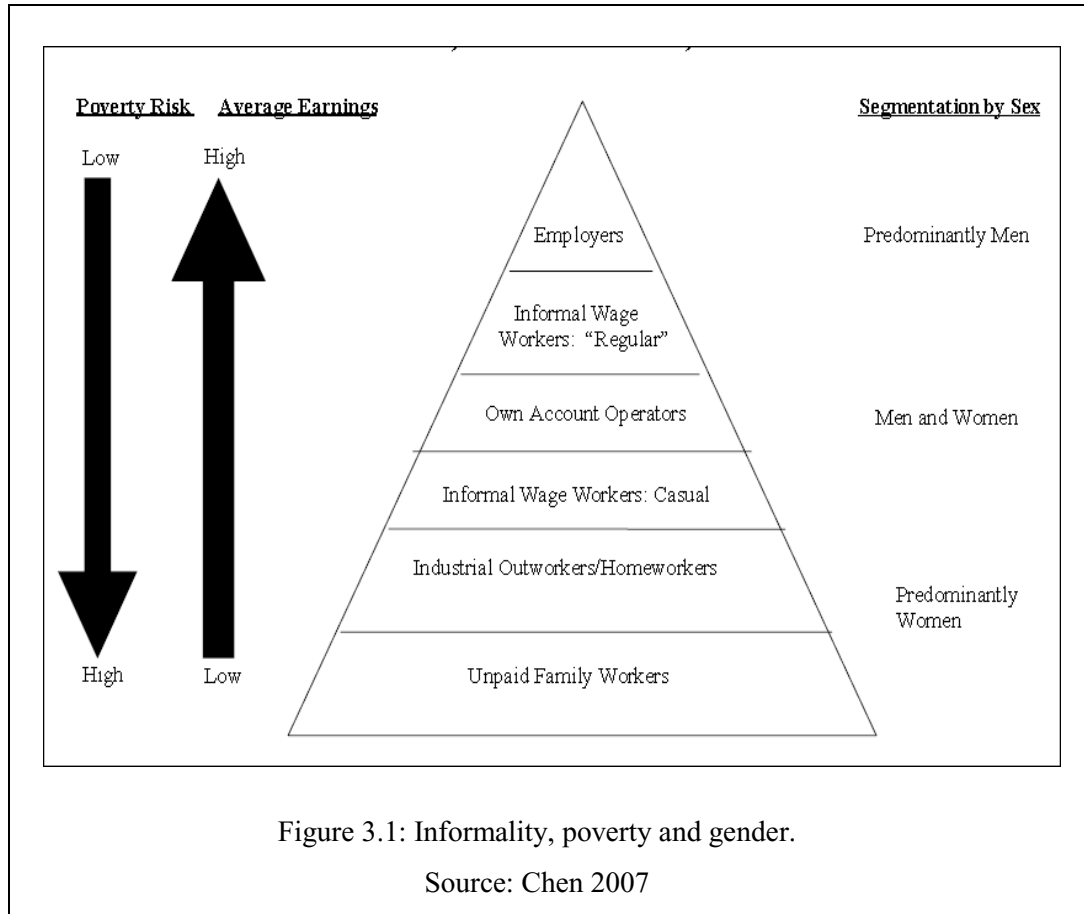
The "iceberg" depicts the various segments of the informal economy grouped by employment status: at the tip is the most visible and the best known segment – the employers/micro-entrepreneurs; and at the base is the least visible and the least understood segment – the industrial homeworker. From micro-surveys and official statistics of the informal economy two facts have been established – firstly, men tend to be overestimated at the tip of the "iceberg" and women tend to be overrepresented at the base of the "iceberg". The share of the men and the women in the intermediate segments tend to be equal. The second observation is that average income or earnings tend to

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decline as one move down from the tip to the base of the iceberg. In addition, women tend to earn less even within specific segments of the informal economy due to gender differences in wages and earnings on the basis of the type of activity and the volume of work or output (Chen 2007).

In the background of the global economic slowdown, better economic estimates, with special emphasis on the inclusion of informal economy estimates in the official measures, assumes great importance for the formulation of policies and programs at the national and international level to promote decent conditions of work, and comprehend the contributions of informal economy towards the economic growth of the countries. Moreover, any efforts at reducing poverty levels and making progress towards the achievement of the MDGs would require better and updated economic statistics.

3.5 Nighttime Lights as a Proxy Measure of Economic Activity –

Remote sensing data in the form of nighttime light images are uniquely poised to map the spatial distribution of urban settlements, population, and economic activity. This is because unlike daytime satellite imagery, nighttime imagery offers a view of visible radiation emitted from only human activities at night.

3.5.1 Background of the Nighttime Lights Data –

Since 1972, the U.S. Air force Defense Meteorological Satellite Program (DMSP) has operated satellite sensors (Operation Linescan System – OLS) capable of detecting Visible and Near InfraRed (VNIR) emissions from cities and towns. The DMSP platform

was originally designed as a meteorological satellite. The OLS is an oscillating scan radiometer acquiring global daytime and nighttime imagery of the earth in the Visible and Near InfraRed (VNIR– 0.4 -1.1 μm) and the Thermal InfraRed (TIR -10.5 - 12.6 μm) band. The OLS visible band data have 6-bit quantization, with digital numbers ranging from 0 to 63. The thermal band has 8-bit quantization. The VIS band signal is intensified at night using a photomultiplier tube (PMT), and this enables the detection of faint VNIR emission sources. The PMT system was set up for the detection of clouds at night, but the light intensification of the PMT system made it possible to detect lights from human activities – lights from cities and towns, gas flares, fires, and fishing boats. The DMSP satellite flies in a sun-synchronous orbit, at an altitude of about 833 km above the earth's surface with nighttime overpasses typically between 8 pm to 10 pm range local time. The DMSP-OLS has a swath width of 3000 km and orbits the earth 14 times a day. Resolution of the fine data collected by the DMSP-OLS is 0.56 km, which is smoothed onboard into 5 x 5 pixel blocks, and so the operational data collections have a spatial resolution of 2.7 km.

The immense potentiality of the nighttime lights data for the observation of human activities on earth was first noted by Croft (1973, 1978, and 1979). Nonetheless, no digital archive was available for the first 20 years, and the data were available only as film strips. These film strips of nighttime lights were used by Welch (1980) and Foster (1983) in their studies, and were later used by Sullivan (1989) to produce a 10-km spatial resolution global image of OLS-observed VNIR emission sources. These data were

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digitally archived only since 1992 by the U.S. Department of Defense (DoD) and the National Geophysical Data Center, of the National Oceanic and Atmospheric Administration (NGDC, NOAA).

3.5.2 Types of nighttime light images –

The Earth Observation Group (EOG), NGDC, NOAA at present produces four types of nighttime lights data collected from the dark half of the lunar cycles. Each of the nighttime lights products are cloud-free composites of large numbers of nighttime orbital segments. The four types of products are as follows:

(i) Average composites – The average lights composite products are generally created for one year or for one month, but they can be created for any specified time period. At first, all available OLS orbits for the specified time period are cropped to include scan lines containing only nighttime data. Then these data are run through a series of algorithms and are flagged on a pixel-by-pixel basis to identify – clouds, lights, glare, bad scan line/lightning, daytime, nighttime marginal quality, zero lunar illuminance, fixed gain and no data coverage. Clouds are identified as areas in the OLS thermal band data that are significantly cooler than reference surface temperature grids. Lights are identified by passing a specialized local sigma filter through the OLS visible band data. Pixels are flagged as lights if they have values greater than the computed background's mean plus N*standard deviation. Each of the OLS nighttime orbits along with the flag data is projected into a 30 arc-second grid. Each input orbit is also screened for abrupt

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gain changes and the presence of aurora. The final OLS products are then generated using the flag data and the pairs of lines selected by the analyst. The compositing routine creates a set of output files of which the average composites are the average of the visible band values. The average composites are produced by dividing the sum of the cloud-free visible band values by the number of cloud-free coverages. The brightness variation of the average composites data is recorded as digital numbers (DN) with values between 0 and 63 (K.E.,Baugh, unpublished material).

(ii) Stable lights composites – When the average composites are made from a year's data collected by a single satellite, there are usually enough cloud-free coverages to identify and remove ephemeral lights from fires and lightning, and other background noises, generating a "stable lights" product. Fires are identified as outliers by running algorithms on the cloud-free nighttime visible band data that are free of solar and lunar illumination and glare. Background areas that are devoid of lighting are defined by a manually drawn mask. Statistics derived from grid cells under the background mask are used to set local thresholds for the stable lights (Elvidge et al. 2009a). Thus, the final stable lights data are produced with average DN values ranging between 0 and 63.

(iii) Radiance-calibrated nighttime image - The stable lights products are characterized by saturation of data in the city centers. In order to overcome the problem of saturation, in early 1996, NGDC requested the DMSP Program office to acquire OLS data at fixed gain settings based on pre-flight calibration and with onboard along scan

gain control (ASGC). Different gain settings were tested and data were finally acquired at gain settings of 24 decibel (dB) and 40 dB (Elvidge et al. 1999). Collection of data at these fixed gain settings produced the first radiance-calibrated nighttime image for the years 1996-1997. The recent versions of fixed gain data are collected at gain settings of 15 dB, 35 dB, and 55 dB. Images produced at these three gain settings are combined by setting thresholds for each of the gain settings, to produce the combined radiance-calibrated image. NGDC is working on producing a new version (using improved algorithms) of radiance-calibrated nighttime images for the years 1999, 2000, and 2003. The radiance-calibrated image of 2006, based on the new algorithms, was completed recently.

The radiance-calibrated nighttime lights have advantages over the stable lights. The radiance-calibrated low-gain data product provides a much better image for the study of the internal structure of cities as it enables the examination of spatial detail associated with brightness variations within urban centers and separate zones within the metropolitan area (Elvidge et al. 1999).

(iv) Merged radiance-calibrated and stable lights product – In an attempt to make superior products and overcome the problems of stable lights data, NGDC has started making merged radiance-calibrated and stable lights products. The first year for which this was done was for 2006. The stable lights data of 2006 were blended with the combined radiance-calibrated image of 2006 through a regression between the 55 dB fixed gain image and the stable lights image.

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3.5.3 Usefulness of the nighttime light images as a proxy measure of socio-economic activity –

Nighttime light images can act as a proxy measure of socio-economic activity and this has been established in several studies. Models developed by using nighttime light images in conjunction with comparatively more reliable socio-economic censuses for developed countries can be applied to countries which do not have the financial and/or institutional sources to conduct detailed censuses (Sutton et al. 2003). In chapters four and five, parameters derived from models developed on the basis of nighttime lights and reliable official statistics of the U.S. have been 'blindly' applied to Mexico and India, respectively, to estimate the formal and informal economic activities of those two countries. This way the nighttime lights can provide an independent, unbiased and objective estimate of socio-economic variables, which are not influenced by the political and economic circumstances of countries (Min 2008).

Nighttime lights data are available in raster format at a spatial resolution of approximately one km^2. Mapping of economic activity based on the nighttime lights allows for aggregation to different levels of administrative units – city, regional, state, or national level; or physical and ecological units, such as, watersheds, or soil and vegetation zones. By enabling estimation of *GDP* data at the city or regional level, maps of economic activity from nighttime lights would make it possible to study the impacts of various economic growth measures which are undertaken in those units. For a scientific understanding of the connections between the socio-economic conditions of countries and their impacts on the physical environment it maybe necessary to integrate socio-economic data with physical and environmental data. Since most of the environmental

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data, for example, global land cover/land use, elevation data, climate, soil and vegetation data, are available in raster formats, the availability of economic maps based on nighttime lights in a gridded format would allow easy integration of economic data with other environmental and physical datasets across administrative boundaries. Creation of a disaggregated (raster or pixel-based) map of total economic activity, including both formal and informal economic activity has been attempted in chapter six of this dissertation.

Another major advantage of the nighttime lights data is more frequent availability in comparison to national income measures. Thus, they can potentially provide a much earlier signal of the growth changes in the country in comparison to national accounts statistics. Also, because of the frequency of availability of the nighttime lights data, the maps showing distribution of wealth or income which are created using the nighttime lights data can be updated on an annual or a semi-annual basis. The DMSP-OLS nighttime images could be used to define the spatial distribution of economic activity on a global basis at a fraction of the data volume and processing than what would be required for conducting similar surveys with Landsat and other high spatial resolution sensors (Elvidge et al. 1997).

3.5.4 Studies relating nighttime lights with economic activity –

The pioneering study of relating nighttime lights and economic activity was done by Elvidge et al. (1997). They used the stable lights data of 1994-95 to analyze the relationship of lit area with population, *GDP*, and electric power consumption of twenty-

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one countries at different levels of economic development. They found a stronger log-linear relationship of lit area with electric power consumption and *GDP* than population. Doll et al. (2000) expanded on Elvidge's analysis to create the first disaggregated *GDP* map at one degree resolution based upon the log-linear relationship between lit area and official purchasing power parity (PPP) *GDP* of countries. The total *GDP* of the world was estimated to be 22.1 trillion dollars, which was about 80 percent of the World Resource Institute's International dollar value of 27.7 trillion dollars for 1992.

The correlation between nighttime lights and per capita *GDP* was further explored by Ebener et al. (2005) with an objective of distributing health resources on the basis of levels of economic development of countries at the national and sub-national level. They used different parameters to test the relationship and found that the total and mean frequency of lights to be better correlated with per-capita *GDP* than lit area. Analysis was also carried out by grouping the countries on the basis of climatic type and the percent of contribution of agriculture towards *GDP*. Grouping the countries according to their agricultural level resulted in a better prediction of per capita *GDP* than grouping them by climatic type at the national level. However, this method did not provide reliable estimates at the sub-national level.

Sutton et al. (2007) tested two separate methodologies using the stable nighttime lights data of 1992-93 and 2000 and LandScan population data to estimate sub-national *GDP* for India, China, Turkey and the United States. The first approach was based on summing the light intensity values, but this approach gave rise to problems associated with saturation of pixels of stable lights data. The second method was based on a non-

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linear relationship between population and areal extent to develop a proxy measure of *GDP*. A regional parameter was also derived from errors in the 1992-93 data and was applied to the 2000 data. The 'urban population' approach was demonstrated to be a better method for estimating sub-national *GDP* than the 'sum of lights' approach. The results also suggested that the use of population information provided by the LandScan dataset in estimating economic activity at the sub-national level greatly improved aggregate national estimates.

In a very recent study, Henderson et al. (2009) used the change in night light intensity between 1992-93 and 2002-03 to measure income growth of 36 countries which are perceived as having low capacity in generating trustworthy national income accounts and are given a grade D (having a margin of error of 40 percent) in the Penn World Tables. Henderson et al. developed a statistical model to optimally combine data on changes in night time lights with data on measured income growth to improve estimates of true income growth. When comparing their estimates with the World Development Indicators (WDI) growth rates, lights seemed to provide a much more accurate measure of growth rates in the context of the known social, political and economic situation of the countries. They also performed an analysis to examine how rainfall shocks affected productivity gains in local agriculture and this in turn affected increase in economic activity as measured by nighttime lights for 541 African cities served by local agricultural hinterlands.

The radiance-calibrated nighttime image of 1996-97 was used by Sutton and Costanza (2002) to create a 30 arc-second (one km^2) image of global marketed economic

activity. The global map of *GDP* was prepared on the basis of a log-log relation between the amount of light energy (LE) emitted by that nation as measured by nighttime light images and the official *GDP* at the nationally aggregate level. The R^2 was found to be 0.74. Since Sutton and Costanza (2002) did not consider this to be a significantly strong correlation, they created nationally specific ratios of *GDP* and LE for each nation of the world and applied it to the global nighttime satellite image to create an image of \$*GDP* per km^2 per year.

Doll et al. (2006) used the 1996-97 radiance-calibrated image to create disaggregated maps of economic activity for the U.S. and 11 European Union countries at five km^2 resolution using linear relationships between total radiance and Gross Regional Product (GRP). These maps were produced by excluding areas with anomalously high levels of economic activity for the amount of total radiance present (usually the capital cities or the largest cities in those countries) and were treated separately from other areas of the map.

The nighttime lights data have also been used in conjunction with the LandScan population data to identify the areas of poverty in the world, where economic activity is limited. By overlaying the LandScan population data and the nighttime lights data it was observed that in comparison to the developed countries, the developing countries of the world had much less lighting relative to their population numbers. This gave rise to the idea of using the quantity of lighting per person as an indicator of poverty levels. A poverty index was developed by dividing the population count by the brightness of the DMSP lights and a calibration was developed using the World Bank's percentage of people living on \$2 a day. This relationship was then used to estimate poverty count in

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each grid cell. This created the first 30 arc-second poverty grid which was aggregated to obtain estimates of poverty at the national and sub-national levels. The total population in poverty as estimated from this method was 2.3 billion people, which compares closely with the World Bank estimates of 2.6 billion. However, there were certain regions of major discrepancy probably because of the cultural differences in lighting – although Egypt's official poverty estimate is 43.9 percent, the estimate derived through this method was only 6.7 percent. Additionally, poverty levels were overestimated for the U.S. states of Vermont and Maine because of perhaps limited use of outdoor lighting (Elvidge et al. 2009b).

Building upon these previous studies, the following two chapters present research on the estimation of formal and informal economic activity of Mexico and India based on models developed relating spatial patterns of lights and official measures of economic activity in the U.S. The sixth chapter deals with the creation of a disaggregated *GDP* map of the world.

CHAPTER 4

ESTIMATION OF MEXICO'S INFORMAL ECONOMY AND REMITTANCES USING NIGHTTIME IMAGERY

4.1 Economic history of Mexico – causes for the increase of informal economic activities in Mexico -

The growth of informal economy in Mexico is related to the liberalization of its economy from the 1980s onwards. Mexico had the import substitution industrialization (ISI) development model for four decades (1940-1980s). The ISI model was widely successful and increased industrial production rapidly. However, the rural economy fell into a deep slump after 1960 and in 1982 the ISI model collapsed. Following its economic collapse during the first half of the 1980s, Mexico joined the General Agreement of Tariff and Trade (GATT) in 1986 and liberalized its national economy. This was followed by the signing of the North American Free Trade Agreement (NAFTA) with the United States and Canada in 1994. NAFTA advocates neoliberal policies with liberalization of trade and investment with the U.S. and Canada, stimulate export-oriented manufacturing sector with an increased U.S. foreign investment and was expected to generate employment indirectly. However, the export-oriented model adopted by Mexico made the country vulnerable to foreign penetration and gave rise to an era of new economic crisis.

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The export-oriented model did not spur economic growth and in fact the country experienced a new economic recession in 1994-95. No new jobs were created in the formal sector, and the excess labor force had to find employment in the informal sector as a last resort.

The causes for the slowing down of industrialization, shrinking of the domestic market, and the increase of informal economic activities as a result of liberalization of the economy were probably the excessive capital-intensive manufacturing development, reorganization of economic activities through the introduction of high technology and a production strategy catering more to the global demand than meeting the local needs. The incorporation of Latin America in the global capitalist economy created a new international division of labor and in an attempt to reduce production costs at a time of intense global competition, organized labor was replaced by an increase in disguised waged labor through the informal sector. The labor markets of the largest metropolises of the country experienced a precarization of the labor conditions, which means less labor stability, replacement of permanent jobs by part-time occupations, and sub-contracting of jobs to small economic units (mostly informal) by middle and big size firms to avoid labor legislation. This trend has been observed in Latin America since the 1980s and has intensified in the recent years.

With liberalization in the first half of the 1990s there was a decline in the manufacturing sector and an expansion of the tertiary sector. However, this expansion in the tertiary sector was mainly observed in the consumer services, which are associated with self-employment, low qualifications and low investments and include the personal

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services, retail, services in hotels and restaurants, food preparation within and without premises, and transport and communication. The producer services, such as wholesale, real estate, financial and professional services, which require more qualified laborers and a fair amount of capital to perform their activities, lagged behind. There was also a proliferation of small businesses with less than five workers (Aguilar 1997).

4.2 Development of alternative measures of informal economy and remittances for Mexico from the nighttime lights imagery -

Because of the problems associated with estimating the magnitude and spatial distribution of economic activity as discussed in the previous chapter (chapter three) alternative methods for estimating the values of informal economy and remittances was explored using known relationships between the spatial patterns of nighttime satellite imagery and economic activity in the U.S. Using the arguably more reliable statistics of Gross State Product (*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) a model was developed 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 Mexican states and the results were compared to the official *GSP* and Gross National Income *(GNI)* statistics, informal economy and remittances to estimate the contribution of the informal economy and remittances towards the *GNI* statistic of Mexico.

Since the official statistics of *GSP*, *GDP*, and *GNI* are believed to include most of the formal transactions in the economy, any excess of these economic values measured from

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the spatial patterns of nighttime lights can be attributed to informal economy and inflow of remittances, which are often underestimated in the official figures. When people are engaged in informal economic activities, especially in developing countries, the income earned improves their economic conditions and purchasing power. With the increase in purchasing power of the individuals, it can be assumed that individuals would make an effort to improve their standard of living and would acquire the basic amenities of modern day living, including electricity. Thus, the spread of electricity can be an indicator of economic development, and is manifested through a spread of electrification in cities, towns, and villages. The spread of electricity consumption, and consequently the level of economic development, can be estimated from the DMSP-OLS nighttime images. Thus, with the official measures accounting for the recorded formal activities, it can be assumed that the underestimated informal economy and flow of remittances into the economy can be estimated from the excess of economic activity measured from the nighttime lights.

Methods -

4.3 Data Used –

4.3.1 Radiance-calibrated nighttime satellite imagery data

The global radiance-calibrated image acquired from 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

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was 1.35 x 10^{-10} watts/cm^2/sr, and the saturation radiance was 8.54 x 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 x 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 4.1). This was necessary as area estimates of the lit urban regions for the analysis were acquired from the DMSP-OLS image. The latitudinal extent of the dataset is from 75˚N to 65˚S and longitudinal extent is from 180˚W to180˚E.

Figure 4.1: Radiance-calibrated nighttime image of 2000-2001, Mexico in the inset.
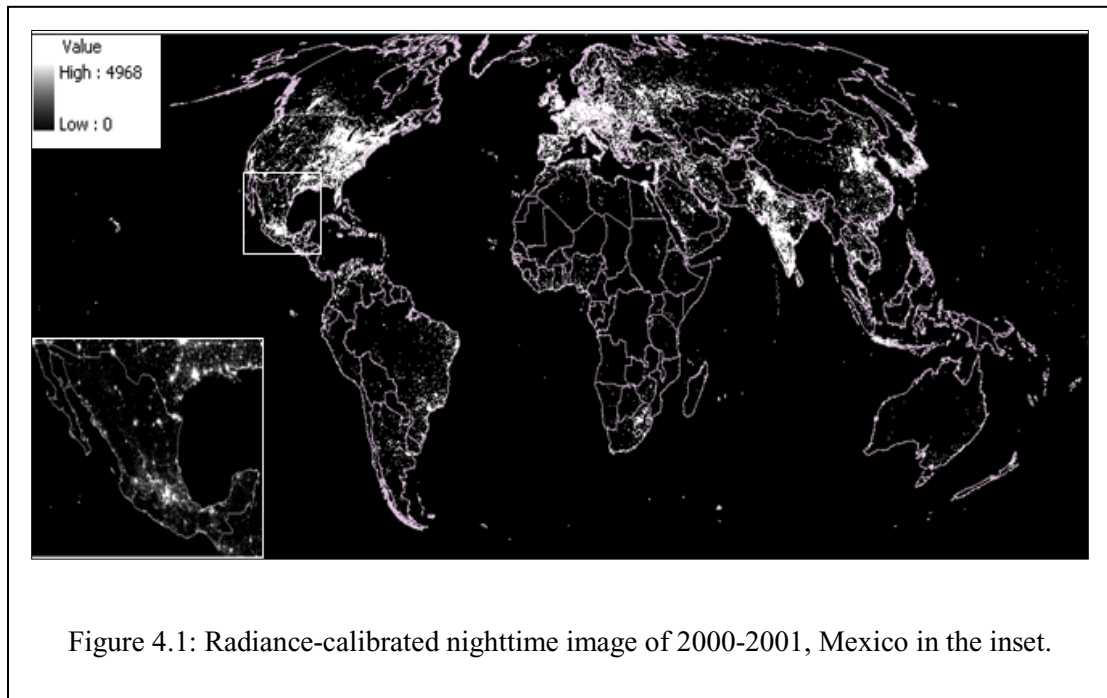
4.3.2 LandScan population data –

The LandScan population dataset for the year 2000 was used to estimate population of the demarcated urban areas in this study. The U.S. Department of Energy, Oak Ridge National Laboratory has been producing a progressive series of spatially disaggregated global population count datasets. The LandScan model uses spatial data and image analysis techniques along with multi-variable dasymetric modeling approach, to apportion sub-national level census counts to each grid cell based on proximity to roads, slope, land cover, and other information, within an administrative boundary. The cells have integer population counts representing ambient population distribution, that is, a population estimation that takes into account the movement of people for work or travel and not only where people sleep. The dataset has a spatial resolution of 30 arc-seconds, or approximately one km^2 near the equator. The data are output in a geographical coordinate system, World Geodetic System (WGS) 1984 datum (LandScan). Because the data are in a spherical coordinate system, cell width decreases in a relationship that varies with the cosine of the latitude of the cell. For this particular analysis the northern latitudinal extent of the LandScan data was cropped to 75˚N (originally extends to 84˚N) and the southern latitudinal extent was cropped to 65˚S (originally extends to 90˚S) to match with the latitudinal extent of the nighttime lights data (figure 4.2).

Figure 4.2: LandScan population data, 2000, Mexico in the inset.
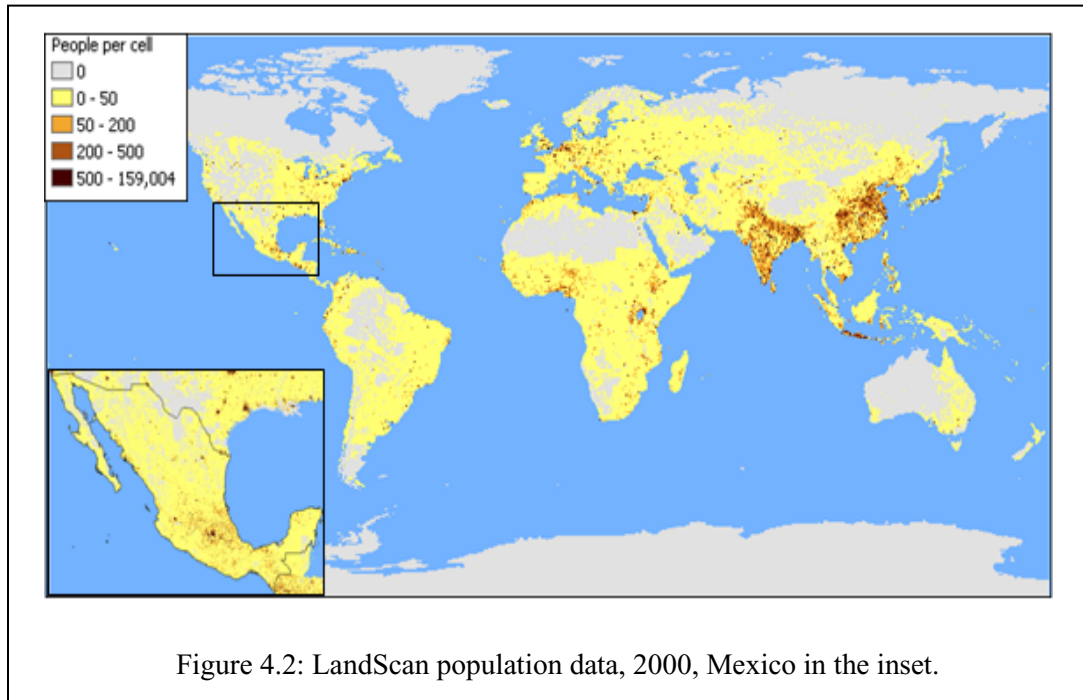
4.3.3 Official statistics of the *GDP*, *GNI* and *GSP* of the U.S. and Mexico -

Tables 4.1 and 4.2 illustrate the inconsistencies between different *GDP* and *GNI* statistics for the U.S. and Mexico that are derived from different sources and/or through the application of different computing methods. For example, the U.S. *GDP* statistics range between U.S. $9,749 billion and $9,883 billion, while Mexico *GDP* statistics range between U.S. $521 billion and Purchasing Power Parity (PPP) U.S. $896 billion. This variation in the values underlines the importance of this study, which aims to develop an independent and standardized methodology to estimate the economic activities of a country.

GDP statistics for the U.S. for the year 2000 were obtained from the U.S. Bureau of Economic Analysis (BEA 2000) and the World Development Report 2002 (World Bank 2002). The *GNI* statistic was obtained from the World Development Report 2002 (World Bank 2002) and the second *GNI* statistic 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 Mexico, the *GDP* statistic in Pesos for the year 2000 was obtained from Instituto Nacional de Estadistica y Geografia (INEGI) (INEGI 2000a). In order to show the disparity in the values because of the use of different conversion methods, the *GDP* value was converted into U.S. dollars on the basis of the official exchange rate for 2000, as well as the PPP conversion factor for 2000. Several sources of *GNI* statistics were obtained, including INEGI (INEGI 1999-2004), the World Development Report 2002 (World Bank 2002), and the World Population Data Sheet (Population Reference Bureau 2000) by multiplying the *GNI* per capita with the mid-2000 population. The *GNI* statistics derived from INEGI and the World Development Report were also converted on the basis of the official exchange rate and PPP conversion factor for 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, pers. comm.), and thus were adjusted by adding 10 percent of *GSP* to the *GSP* of each state, a statistic referred to as the Adjusted Official Gross State Product (*AGSP*) (Table 4.5, Column 2). For Mexico, the *GSP* of each state for the year 2000 was obtained from INEGI. These are the *Producto interno bruto por entidad federative, Total*

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de la actividad económica (Gross internal product by Federal Organization, Total of the economic activity) (INEGI 2000a). The *GSP* values were converted into PPP U.S. dollars by applying the PPP conversion factor (PPP U.S. $$GSP_{Mex_i}$) (Table 4.6, Column 2).

In spite of these discrepancies in reported economic indicators, the adjusted *GSP* statistics ($AGSP_{US_i}$) derived from the U.S. Bureau of Economic Analysis were assumed to be the most reliable official statistics 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). All subsequent analysis was based on the $AGSP_{US_i}$ (Table 4.5). Also, since the PPP values are the standard used for international comparisons, the PPP U.S.$ *GNI* value of Mexico (GNI_{Mex}, in bold in Row 3 of Table 4.2) and the PPP U.S. $$GSP_{Mex_i}$ (Table 4.6) were used to facilitate comparison of results.

Table 4.1 Comparison of the *GNI* and *GDP* statistics of the United States from different sources

Row no.	Statistic	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 U.S. Dollars	$ 8,059 billion
3	*GDP*	2000	World Dev. Report 2002	Average official exchange rate of that year	$ 9,883 billion
4	*GDP*	2000	U.S. Bureau of Economic Analysis	Current U.S.$	$ 9,749 billion

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Table 4.2 Comparison of the *GNI* and *GDP* statistics of Mexico from different sources

Row no.	Statistic	Year	Source	Conversion techniques and Currency units	Value
1	*GNI*	2000	INEGI	In Pesos	5,491 billion
2	*GNI*	2000	INEGI	In terms of exchange rate U.S. Dollars	$ 574 billion *
3	***GNI***	**2000**	**INEGI**	**PPP U.S. Dollars**	**$ 886 billion ***
4	*GNI*	2000	World Dev. Report 2002	Atlas Method - using three year average exchange rate	$ 498 billion
5	*GNI*	2000	World Dev. Report 2002	PPP U.S. Dollars	$ 864 billion ▲
6	*GNI*	2000	Population Reference Bureau	In U.S. Dollars	$ 382 billion
7	*GDP*	2000	INEGI	In Pesos	4,984 billion
8	*GDP*	2000	INEGI	In terms of exchange rate U.S. Dollars	$ 521 billion ♦
9	*GDP*	2000	INEGI	PPP U.S. Dollars	$ 804 billion ♦
10	*GDP*	2000	World Dev. Report 2002	Average official exchange rate of that year	$ 575 billion
11	*GDP*	2000	World Dev. Report 2002	PPP U.S. Dollars	$ 896 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

4.3.4 Official measures or statistics of the informal economy and remittances of Mexico -

Measure of the contribution of the informal economy to total *GDP* for Mexico for the year 2000 was obtained from INEGI (INEGI 1998-2003). A state-wise breakdown of the data was not available and only the total contribution of the informal economy towards

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GDP was acquired (Table 4.3). According to INEGI statistics, the contribution of the informal economy towards *GDP* of Mexico for the year 2000 was approximately 12 percent.

Table 4.3 Reported value of the informal economy statistic of Mexico

	Informal Economy (2000)
In Pesos	616 billion
In PPP U.S. Dollars	99 billion

Source: INEGI, *Sistema de Cuentas Nacionales de México, Cuentas por Sectores Insititucionales, Cuenta Satelite del Subsector informal de los hogares*, 1998-2003

The data on the total flow of remittances into Mexico for the year 2000 was obtained from *Banco de Mexico* (Bank of Mexico 2004). The contribution of remittances towards *GNI* for Mexico for the year 2000 was measured to be 0.8 percent, a total value of 6.6 billion dollars.

4.4 Data analysis –

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 4.4). 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 4.3, P'_{US_i} in Table 4.4). In the next step (Stage 2 in figure 4.3), a multiple regression model was developed to estimate

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Gross State Income of the U.S. states ($EGSI_{US_i}$ in Table 4.4) 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 4.4), and (3) adjusted GSP of each U.S. state ($AGSP_{US_i}$ in Table 4.4). Next (Stage 3 in figure 4.3), the same threshold developed in Stage 1 was used to demarcate the urban areas of the Mexican states (A_{Mex_i} in Table 4.4). Urban area was determined, and the 'U.S. equivalent urban population' was estimated using the model developed for the U.S. in Stage 1 (P'_{Mex_i} in Table 4.4). The multiple regression model developed for the U.S. in Stage 2 was used to estimate the Gross State Income for each Mexican state (Stage 4 in figure 4.3, $EGSI_{Mex_i}$ in Table 4.4). $EGSI_{Mex_i}$ for each state was summed to get the Estimated Gross Domestic Income ($EGDI_{Mex}$) for the whole of Mexico. The underestimation of the informal economy and remittances in the official GNI measure (GNI_{Mex} in Table 4.4) was calculated by subtracting the GNI_{Mex} from the $EGDI_{Mex}$ (Stage 5 in figure 4.3, $UIER$ in Table 4.4). Definitions and abbreviations for all the economic variables which were developed and used in different stages of the analysis are presented in Table 4.4.

Table 4.4 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 (i), demarcated by the brightness threshold of 20 x 1.35 x 10 $^{-10}$
P_{US_i}	Population (extracted from the LandScan dataset) of the lit urban areas, demarcated by the brightness threshold, for each U.S. state (i)
P'_{US_i}	Estimated urban population of the lit urban areas, demarcated by the brightness threshold, for each U.S. state (i)
S_{US_i}	Sum of lights of the lit areas for each U.S. state (i)
$AGSP_{US_i}$	Adjusted Official Gross State Product for each U.S. state (i): official GSP is inflated by 10% to account for the contribution of the informal economy

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$EGSI_{US_i}$	Estimated Gross State Income for each U.S. state *(i)*: sum of the formal economy, informal economy and remittances as estimated from the nighttime lights image
Residual$_{USi}$	Residual Percentage for each U.S. state *(i)*, percentage difference between official $AGSP_{US_i}$ and modeled $EGSI_{US_i}$
A_{Mex_i}	Area of the lit urban areas for each Mexican state *(i),* demarcated by the brightness threshold of 20 x 1.35 x 10 $^{-10}$
P'_{Mex_i}	Estimated 'U.S. equivalent urban population' of the lit urban areas, demarcated by the brightness threshold, for each Mexican state *(i)*
S_{Mex_i}	Sum of lights of the lit areas for each Mexican state *(i)*
GSP_{Mex_i}	Official Gross State Product of each Mexican state *(i)*
$EGSI_{Mex_i}$	Estimated Gross State Income for each Mexican state *(i)*: sum of the formal economy, informal economy and remittances as estimated from the nighttime lights image
$EGDI_{Mex}$	Estimated Gross Domestic Income of Mexico (sum of *EGSI* for all states)
GNI_{Mex}	Official Gross National Income of Mexico
$UIER$	Predicted underestimation of informal economy and remittances in the official statistic of *GNI*

Figure 4.3: Overview of the model to predict the underestimation of informal
economy and remittances in Mexico's official *GNI* statistic.
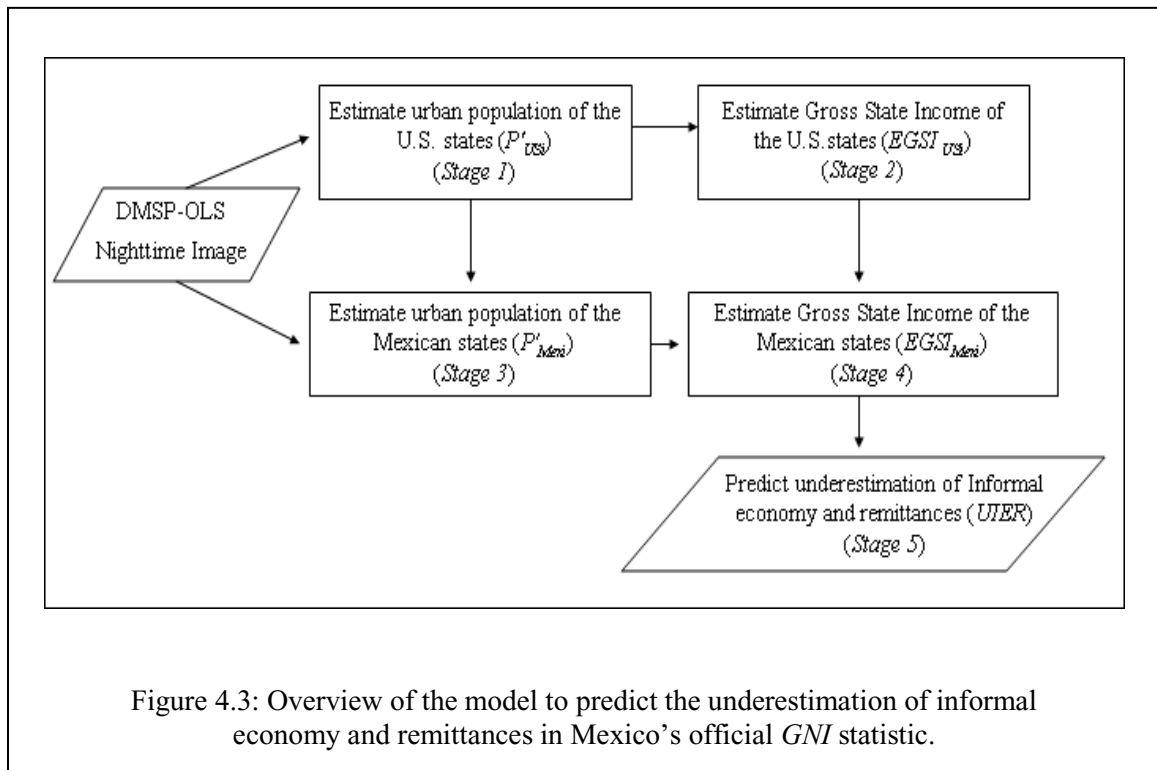
4.4.1 Basic assumptions of the model -

The model developed to estimate the Gross State Income for each Mexican state ($EGSI_{Mex_i}$), Gross Domestic Income ($EGDI_{Mex}$), informal economy and remittances for Mexico was trained using the more 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 *GSP* data are either unavailable or simply do not exist, estimates of urban populations can serve as a valid proxy measure of the value of economic activity.

- Economic activity associated with urban populations creates the same spatial patterns of nighttime lights in Mexico 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 Mexico.

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 Mexico to estimate $EGSI_{Mex_i}$ for each Mexican state, national $EGDI_{Mex}$, and subsequently the informal economy and remittances of the Mexican states.

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4.4.2 Model to predict urban population of the U.S. States – Stage 1

The aim of the analysis was to develop a model to estimate the $EGSI_{Mex_i}$, $EGDI_{Mex}$, informal economy and remittances of Mexico based on U.S. parameters. The first stage in the model involved estimating urban population of the U.S. states (figure 4.4), 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:

$$y = ax^b \qquad (4.1)$$

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

$$\ln(y) = \ln(a) + b \times \ln(x) \qquad (4.2)$$

Based on this law of allometric growth, Tobler (1969) established that urban populations (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:

$$\ln(population) = a + b \times \ln(area) \qquad (4.3)$$

The original application of allometric growth law estimated population of individual urban settlements or cities. This application was modified as urban populations of the U.S. and Mexico was estimated 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. Experimentation was carried out 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 Mexico.

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 4.4 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

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48 U.S. states was subsequently estimated by the exponentiation of the logarithmic equation (Equation 4.5) (Sutton et al. 2007). The regression relationship is presented in figure 4.5.

$$\ln(P_{US_i}) = \alpha_{1US} + \beta_{1US} \times \ln(A_{US_i}) \tag{4.4}$$

$$P_{US_i}' = \exp(\alpha_{1US} + \beta_{1US} \times \ln(A_{US_i})) \tag{4.5}$$

Figure 4.4: 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 Mexico in Stage 3.
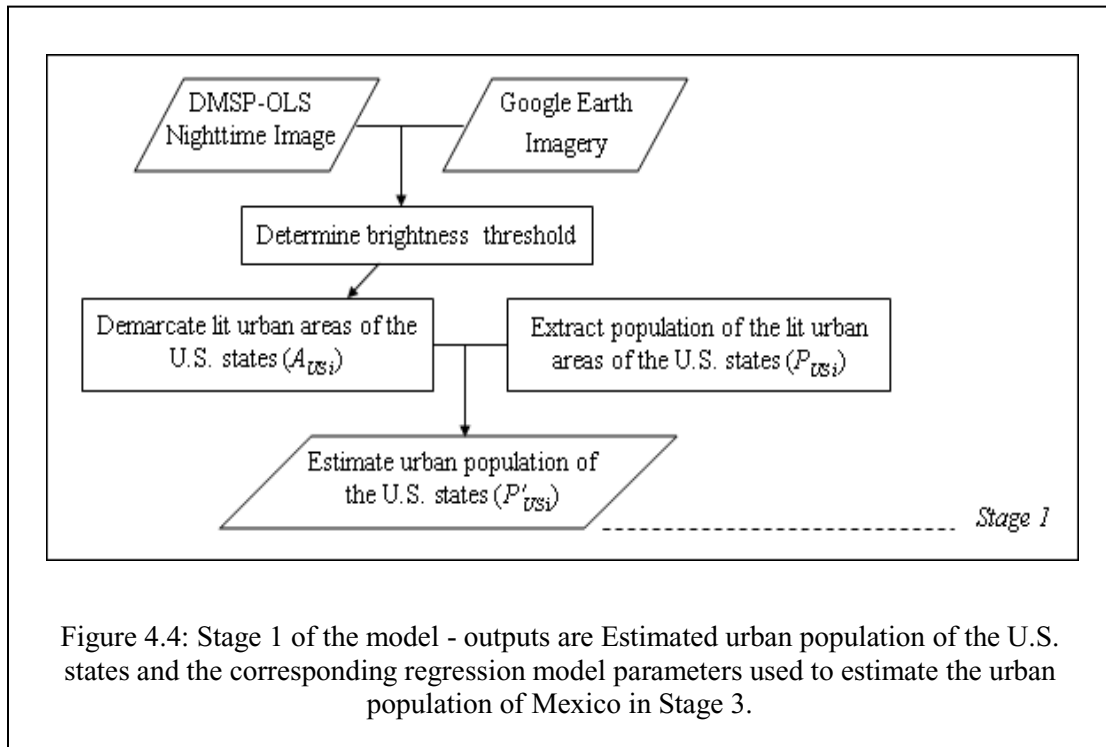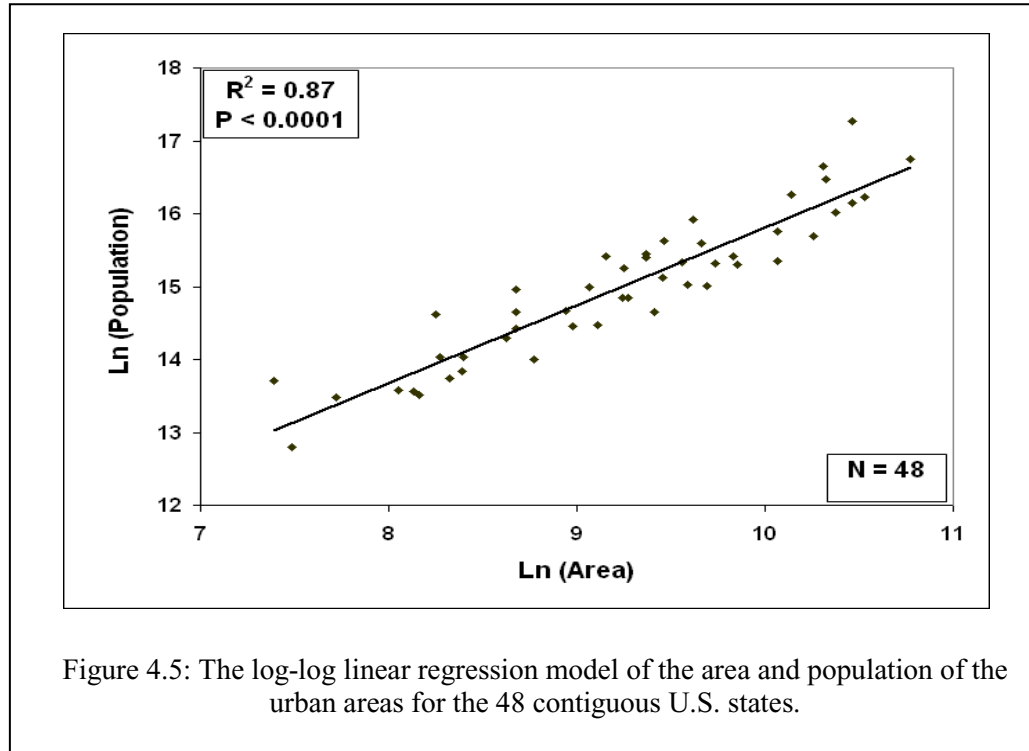
Figure 4.5: The log-log linear regression model of the area and population of the urban areas for the 48 contiguous U.S. states.

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

In Stage 2 (figure 4.6), 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 and activities measured by nighttime lights 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 4.6). 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

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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 4.7).

$$\ln(AGSP_{US_i}) = \alpha_{2US} + \beta_{2US} \times \ln(P'_{US_i}) + \beta_{3US} \times S_{US_i} \qquad (4.6)$$

$$EGSI_{US_i} = \exp(\alpha_{2US} + \beta_{2US} \times \ln(P'_{US_i}) + \beta_{3US} \times S_{US_i}) \qquad (4.7)$$

Figure 4.6: 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 Mexican states in Stage 4 of the model.
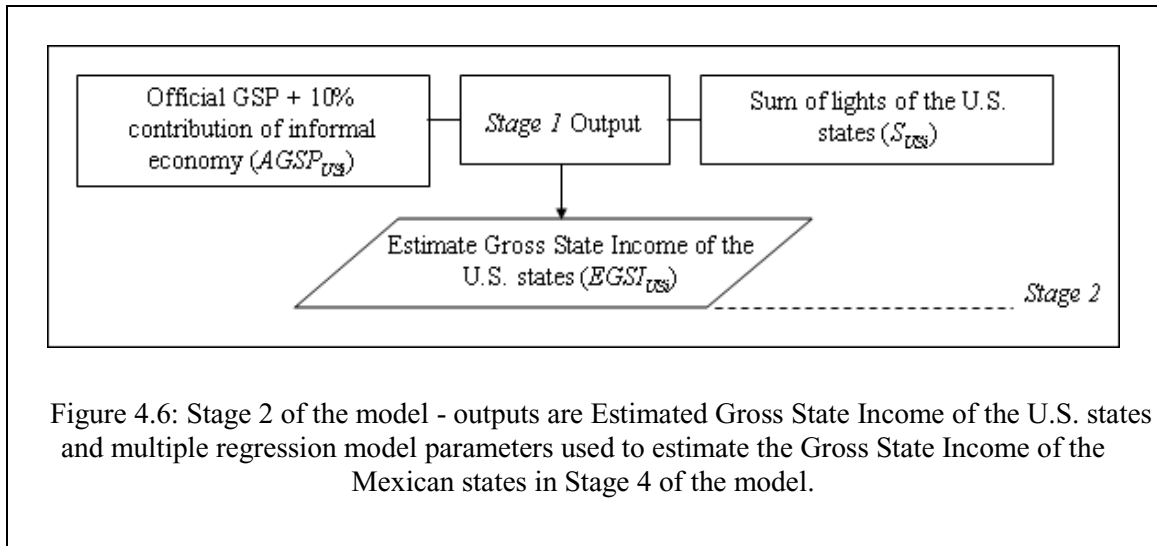
Figure 4.7 presents the Actual-versus-Predicted plot for the log of the $AGSP_{US_i}$ values. When Actual $\ln(AGSP_{US_i})$ (i.e., officially reported statistics) was modeled as a linear

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).

Figure 4.7: 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' are the predictor variables.
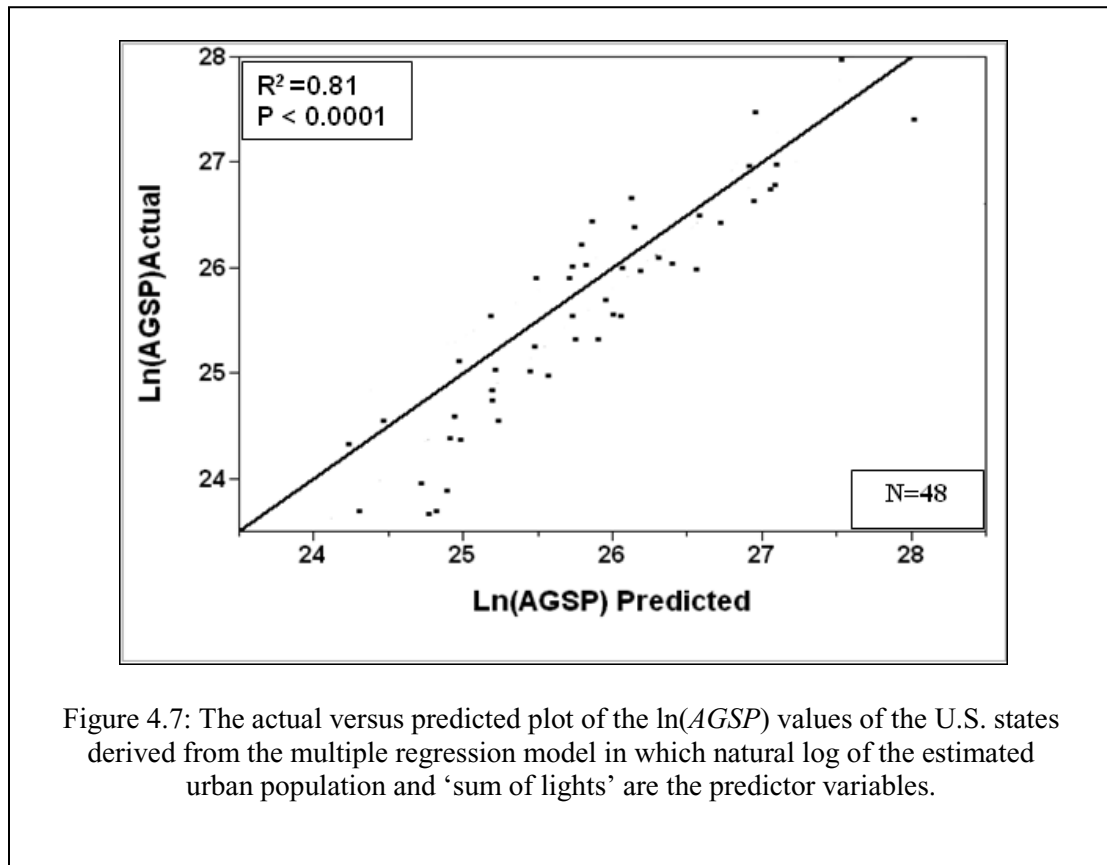
A plot of the official $AGSP_{US_i}$ and modeled $EGSI_{US_i}$ values of the U.S. states is shown in figure 4.8. The correlation coefficient (Pearson's r) between officially reported and modeled estimates is 0.84, indicating a strong association between the two variables. The modeled $EGSI_{US_i}$ values are close to the official $AGSP_{US_i}$ values for most of the states,

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with the exception of Texas, New York and California. $EGSI_{US_i}$ was overestimated for

Texas and underestimated for New York and California.
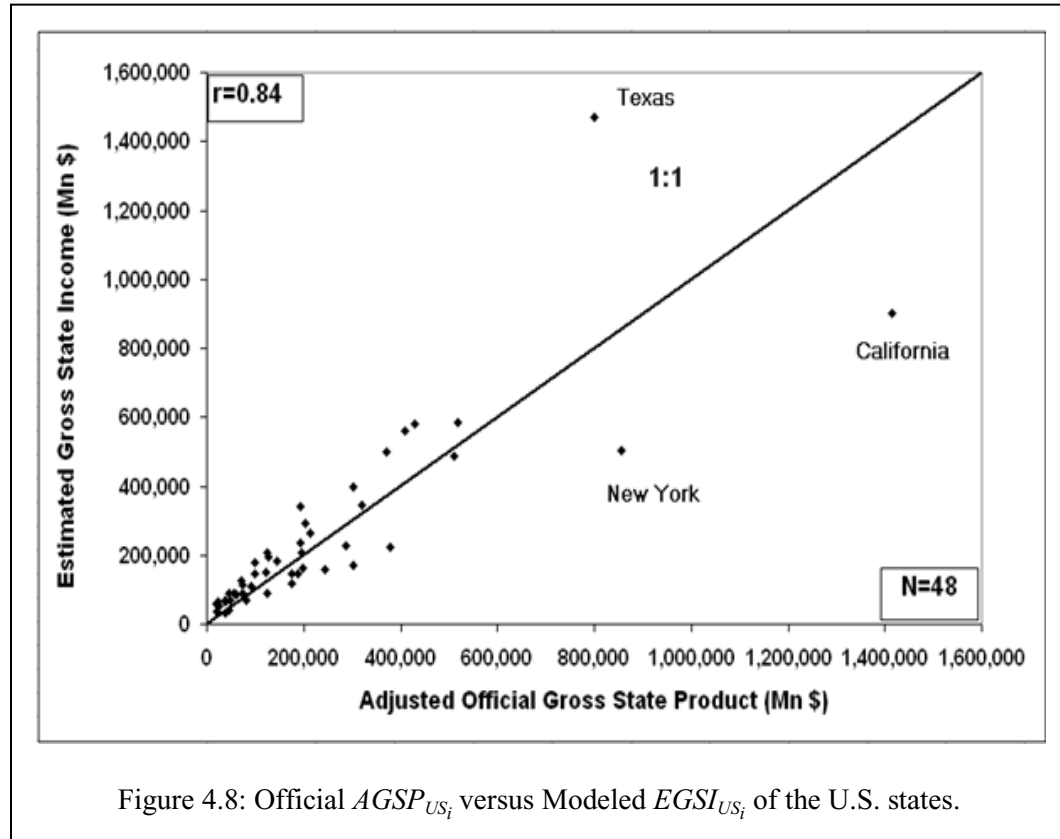
Figure 4.8: Official $AGSP_{US_i}$ versus Modeled $EGSI_{US_i}$ of the U.S. states.

4.4.4 Estimating the 'U.S. equivalent urban population' of the States of Mexico – 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 Mexican states (figure 4.9).

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Figure 4.9: Stage 3 of the model - output is Estimated 'U.S. equivalent urban population' of each Mexican state using the U.S. regression parameters derived from Stage 1.
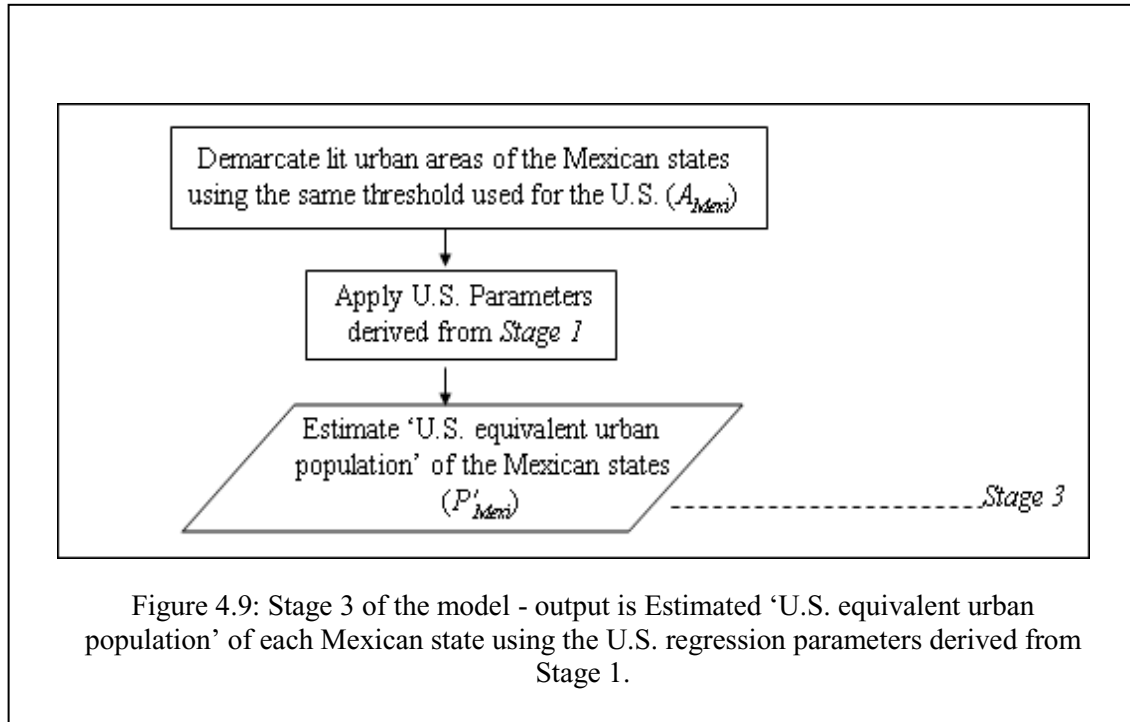
The same U.S. brightness threshold was used to delineate the lit urban areas of Mexico in order to apply the parameters that were estimated for the U.S. and to conform to the assumption that economic activity creates the same spatial patterns of light in the U.S. and in Mexico.

Area of the urban extent for each Mexican state demarcated by the brightness threshold was estimated from the nighttime image (A_{Mex_i}). The regression parameters derived for the U.S. in Stage 1 were applied to Mexico's urban areas to obtain the 'U.S. equivalent population' for the urban areas of each Mexican state (P'_{Mex_i}) (Equation 4.8).

$$P'_{Mex_i} = \exp(\alpha_{1US} + \beta_{1US} \times \ln(A_{Mex_i})) \tag{4.8}$$

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4.4.5 Estimating Gross State Income of the states of Mexico – Stage 4

In Stage 4 (figure 4.10), the Gross State Income for each Mexican state was estimated. The same regression model which was developed for the U.S. was used to estimate the $EGSI_{Mex_i}$ of each Mexican state using the sum of lights for each Mexican state (S_{Mex_i}) and estimated urban population of each Mexican state (Equation 4.9).

$$EGSI_{Mex_i} = \exp(\alpha_{2US} + \beta_{2US} \times \ln(P'_{Mex_i}) + \beta_{3US} \times S_{Mex_i}) \tag{4.9}$$
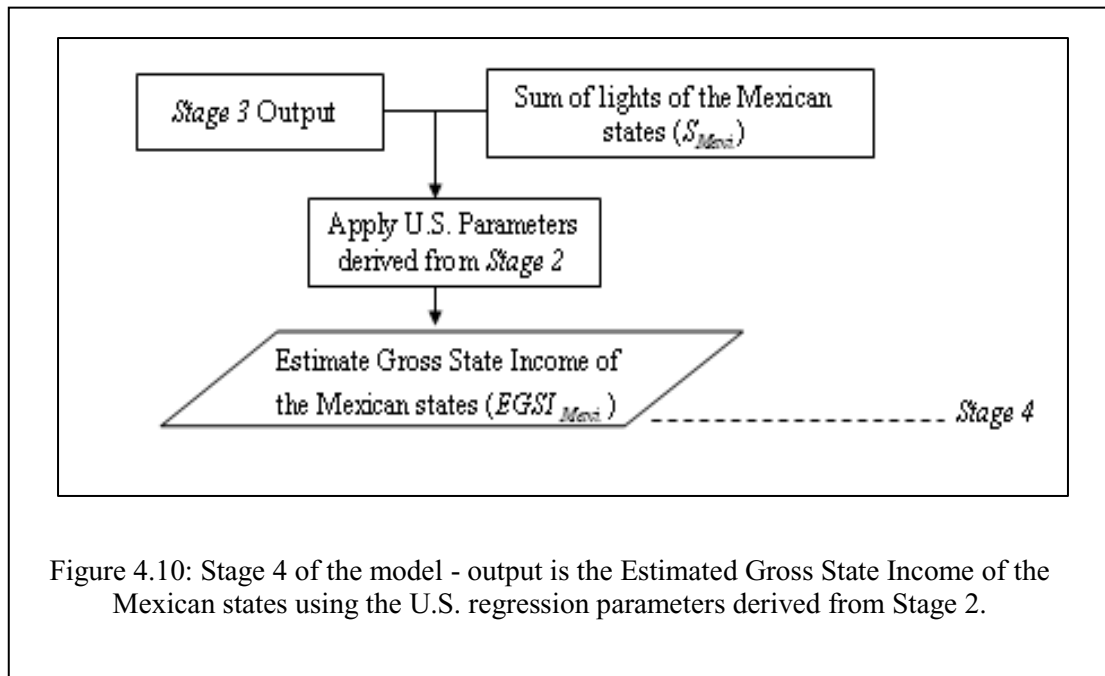
Figure 4.10: Stage 4 of the model - output is the Estimated Gross State Income of the Mexican states using the U.S. regression parameters derived from Stage 2.

$EGSI_{Mex_i}$ of each Mexican state derived from the DMSP-OLS image was assumed to include the formal economy, informal economy, and the estimates of the remittance inflow into Mexico. $EGSI_{Mex_i}$ should therefore be compared to the official *GNI* statistic; however *GNI* values for Mexico are not available at the state level. Additionally, the

contribution of the remittances reported by *Banco de Mexico* is only 0.8 percent of the official *GNI* that is reported by INEGI for the year 2000. Thus, it was concluded that $EGSI_{Mex_i}$ (which was assumed to include remittances) and the official *GSP* values (GSP_{Mex_i}, which do not include remittances) were comparable. In figure 4.11, Modeled $EGSI_{Mex_i}$ was plotted against the official GSP_{Mex_i} for each Mexican state, excluding *Distrito Federal* or Mexico City. However, although Mexico City was not shown in figure 4.11, it was taken into account in the calculation of the national Estimated Gross Domestic Income ($EGDI_{Mex}$) and in the final computation of the underestimated informal economy and remittances. The plot shows that GSP_{Mex_i} was overestimated for 27 of the Mexican states and underestimated for one state. The Pearson's correlation coefficient (r) of the official GSP_{Mex_i} versus modeled $EGSI_{Mex_i}$ is 0.87, indicating a strong association between the two variables.

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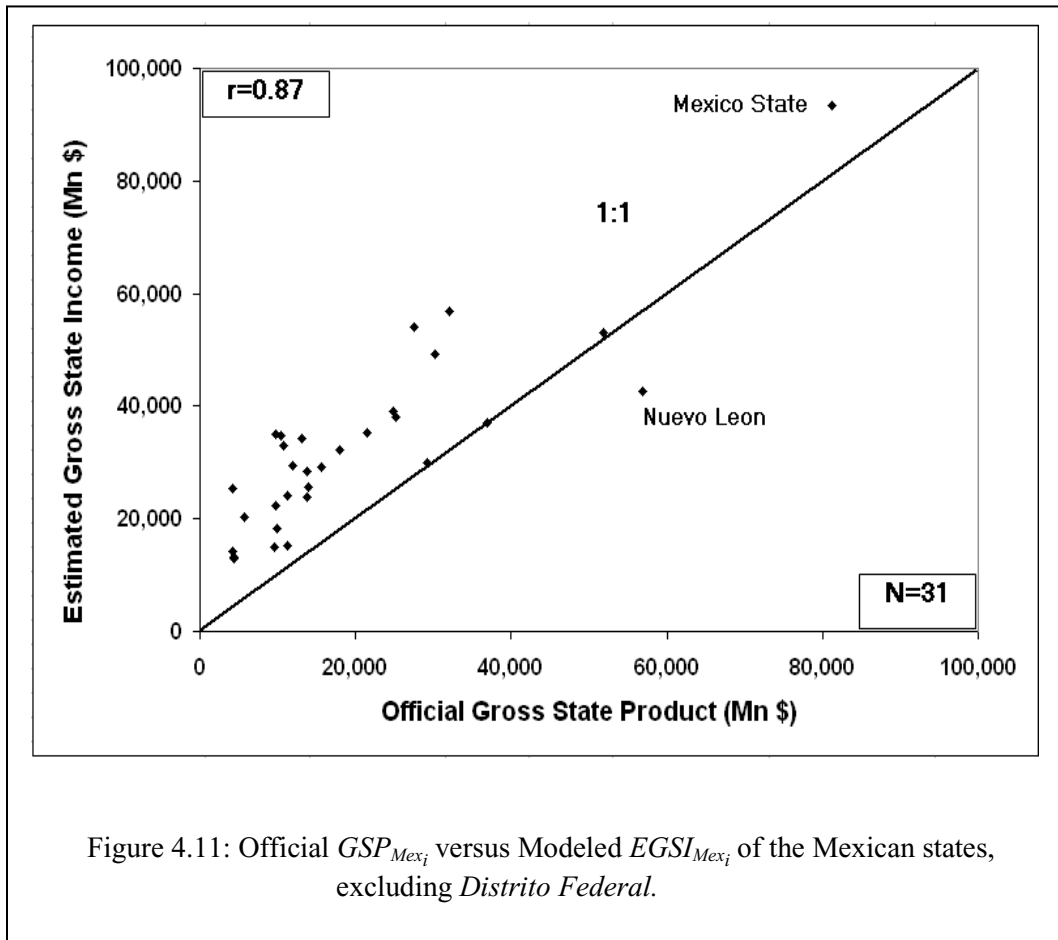
Figure 4.11: Official GSP_{Mex_i} versus Modeled $EGSI_{Mex_i}$ of the Mexican states, excluding *Distrito Federal.*

4.4.6 Estimating the magnitude and spatial distribution of the informal economy and remittances of Mexico and comparing it with the published values – Stage 5

The final stages in the analysis involved estimating the magnitude of informal economy and remittances of Mexico (figure 4.12). The $EGSI_{Mex_i}$ values derived from nighttime lights data for each state were summed to estimate Gross Domestic Income ($EGDI_{Mex}$) for all of Mexico. $EGDI_{Mex}$ was compared to the official GNI value of Mexico (GNI_{Mex}). Both $EGDI_{Mex}$ and GNI_{Mex} include the formal economy, informal economy and

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the inflow of remittances into the economy. It was assumed that remittances are included in the nighttime-lights derived $EGDI_{Mex}$ estimates because the residents of Mexico 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. Subtracting the $EGDI_{Mex}$ from the official GNI_{Mex} gave the predicted underestimation of informal economy and remittances (*UIER*) in the official statistic of GNI_{Mex} (Equation 4.10)

$$UIER = EGDI_{Mex} - GNI_{Mex} \qquad (4.10)$$

Figure 4.12: Stage 5 of the model - output is predicted underestimation of the informal economy and remittances in the official *GNI* statistic.
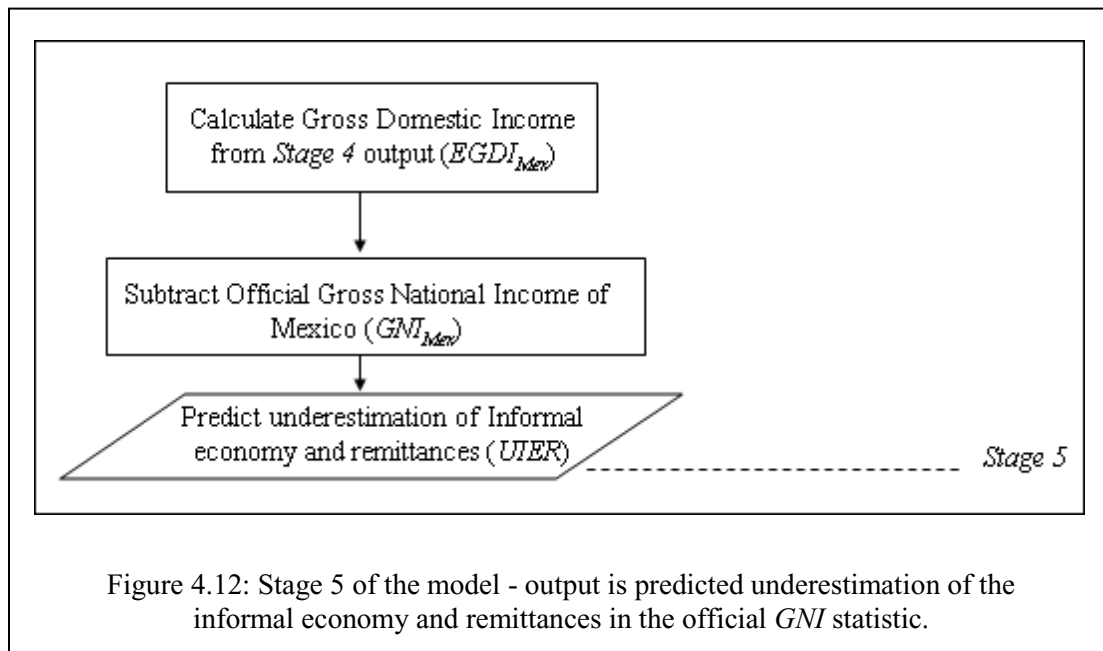
4.5 Results –

4.5.1 Official *AGSP* and modeled *EGSI* 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 U.S. states. 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 (Residual$_{USi}$) was calculated (Equation 4.11, Table 4.5) and mapped in figure 4.13 to get a clear picture of the degree to which the $EGSI_{US_i}$ was over- or underestimated for each state.

$$\text{Residual}_{US_i} = \frac{AGSP_{US_i} - EGSI_{US_i}}{AGSP_{US_i}} \times 100 \tag{4.11}$$

$EGSI_{US_i}$ 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 statistics 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 4.8). These are also the three states with the highest official statistics 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

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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 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.

Table 4.5 Official $AGSP_{US_i}$, Modeled $EGSI_{US_i}$ and Percentage Residual for each U.S. state

U.S. States	Official $AGSP_{USi}$ (Mn $)*	Modeled $EGSI_{USi}$ (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
Mexicona	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

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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. Census Bureau, U.S. Bureau of Economic Analysis, 2000

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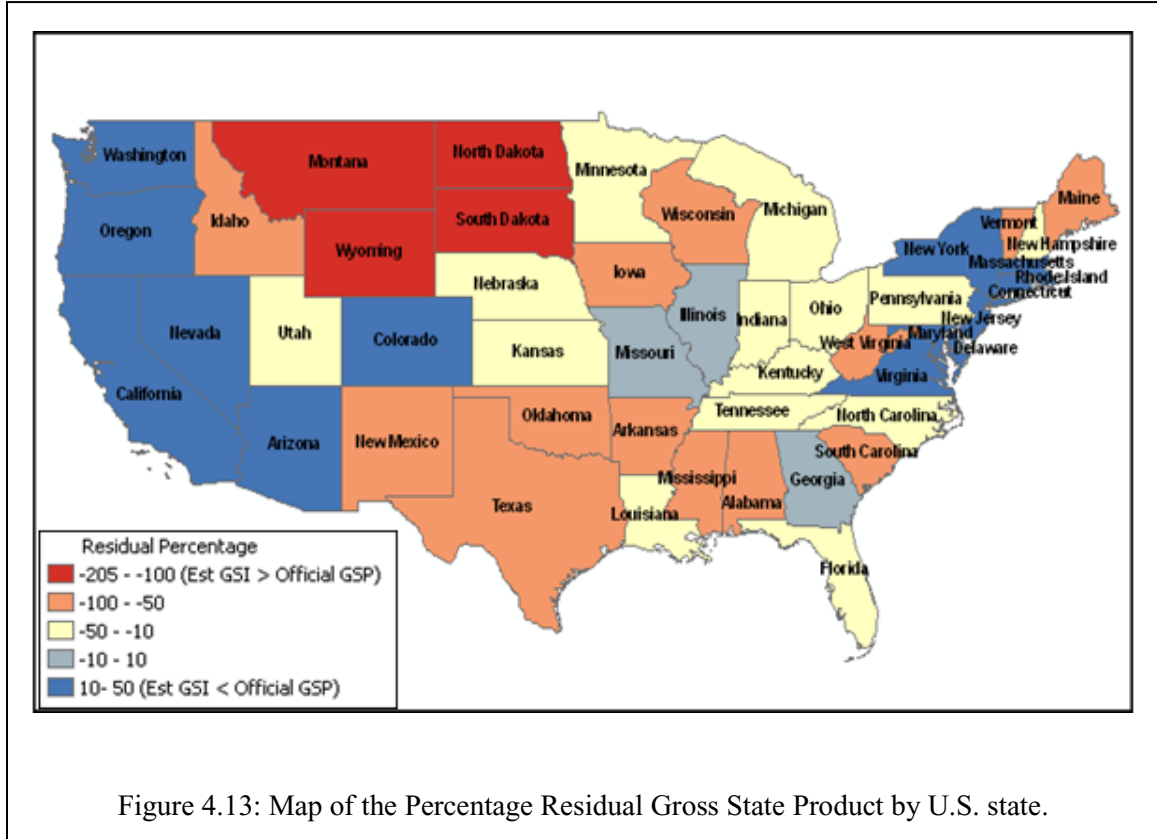
Figure 4.13: Map of the Percentage Residual Gross State Product by U.S. state.

4.5.2 Official *GSP* and modeled *GSI* of Mexico -

The residual percentages of the Gross State Product (GSP_{Mex_i}) of each Mexican state derived from the model using U.S. parameters showed an overestimation of $EGSI_{Mex_i}$ for all the states except for Distrito Federal and Nuevo Leon (Table 4.6). Underestimation of $EGSI_{Mex_i}$ was the greatest for Distrito Federal (86 percent). The percentage residual map of Mexico is shown in figure 4.14.

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Table 4.6 Official GSP_{Mex_i}, Modeled $EGSI_{Mex_i}$ and Percentage Residual for each Mexican state

Mexican States	Official GSP_{Mexi} (PPP U.S. Mn \$)*	Modeled $EGSI_{Mexi}$ (PPP U.S. Mn \$)	Percentage Residual
Aguascalientes	9,948	18,287	-84
Baja California	29,174	30,004	-3
Baja California Sur	4,349	13,050	-200
Campeche	9,606	15,027	-56
Chiapas	13,096	34,176	-161
Chihuahua	36,863	37,157	-1
Coahuila	25,109	38,197	-52
Colima	4,394	13,172	-200
Distrito Federal	180,940	25,270	86
Durango	9,665	22,288	-131
Guanajuato	27,558	54,015	-96
Guerrero	13,819	28,445	-106
Hidalgo	10,479	34,686	-231
Jalisco	51,808	53,011	-2
Mexico	81,147	93,334	-15
Michoacan	17,892	32,160	-80
Morelos	10,728	33,067	-208
Nayarit	4,255	14,286	-236
Nuevo Leon	56,923	42,575	25
Oaxaca	11,916	29,470	-147
Puebla	30,228	49,212	-63
Queretaro	13,925	25,636	-84
Quintana Roo	11,253	15,299	-36
San Luis Potosi	13,834	23,969	-73
Sinaloa	15,576	29,178	-87
Sonora	21,494	35,341	-64
Tabasco	9,721	35,138	-261
Tamaulipas	24,888	39,162	-57
Tlaxcala	4,276	25,332	-492
Veracruz	31,975	56,804	-78
Yucatan	11,166	24,022	-115
Zacatecas	5,784	20,367	-252

- Source: INEGI, *Total de la actividad economica*, 2000

Figure 4.14: Map of the Percentage Residual Gross State Product by Mexican state.
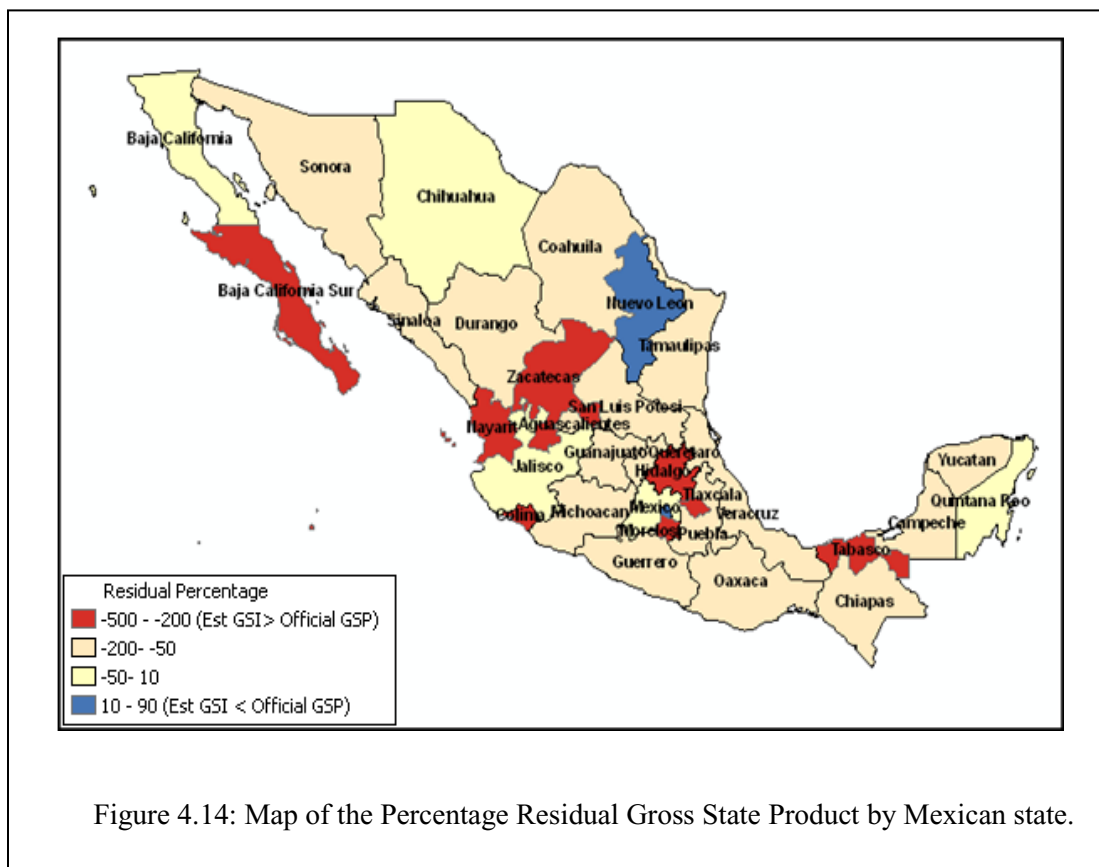
4.5.3 Estimating the magnitude of underestimation of informal economy and remittances in the official statistic of *GNI* of Mexico -

The $EGDI_{Mex}$ of Mexico (sum of the state $EGSI_{Mex_i}$ values of each Mexican state) was approximately U.S. $1,041 billion (Row 1 of Table 4.7). This figure was assumed to include the formal economy, informal economy and remittances. The official *GNI* of Mexico (GNI_{Mex}) for 2000 was approximately PPP U.S. $886 billion (Row 2 of Table 4.7). Subtracting the GNI_{Mex} from $EGDI_{Mex}$ gave the predicted underestimation of informal economy and remittances in the official statistics (Row 3 of Table 4.7). In order to derive the magnitude of underestimation, the official statistics of informal economy

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and remittances for the year 2000 was summed (Row 6 of Table 4.7). Then, the predicted value of informal economy and remittances (Row 7 of Table 4.7) was divided by the sum of the official statistics of informal economy and remittances (Row 8 of Table 4.7). The result demonstrated that the informal economy and inflow of remittances for Mexico was about 50 percent larger than what was recorded in the official statistic of Gross National Income (GNI_{Mex}).

Table 4.7 Determining the magnitude of underestimation of informal economy and remittances in the official statistic of *GNI* of Mexico

Row No.		In U.S. $ billions
1	Nighttime lights Estimated *GDI* of Mexico (*EGDI*$_{Mex}$) (formal+informal+remittances)	1,041
2	Official statistic of the *GNI* of Mexico (*GNI*$_{Mex}$) (formal+informal+remittances) *	886
3	Predicted underestimation of remittances and informal economy *(UIER)*	155
4	Official statistic of Informal economy in 2000 •	99
5	Official statistic of remittances in 2000 ♦	7
6	Total official statistic of informal economy and remittances	106
7	Predicted underestimation of remittances and informal economy	155
8	Total official statistic of informal economy and remittances	106
9	Magnitude of underestimation	~ 50%

* Source: INEGI, Sistema de Cuentas Nacionales de Mexico, Producto interno bruto, a precios de Mercado, 1999-2004

• Source: INEGI, *Sistema de Cuentas Nacionales de México, Cuentas por Sectores Insititucionales, Cuenta Satelite del Subsector informal de los hogares*, 1998-2003

♦ Source: Bank of Mexico, Annual Report, 2004

4.6 Discussion –

The radiance-calibrated nighttime image of 2000-2001 and the $AGSP_{US_i}$ of each U.S. state were used to develop a regression model for estimating $EGSI_{Mex_i}$ for each of the Mexican states. The $EGDI_{Mex}$ was compared to the official statistic of GNI_{Mex}. It was found that most states in Mexico have more lighting compared to what their officially reported GSP would suggest. The idea that this surplus in lighting could be attributed to the informal economy and inflow of remittances in Mexico was explored. It was concluded that the informal economy in Mexico may be larger than the existing official measures (12 percent of GDP) and this has been corroborated in several studies which have used different methods to estimate the informal economy of countries. Schneider and Enste (2000) had estimated the informal economy of Mexico to be varying between 27 percent and 49 percent of GDP using the indirect approaches (Physical Input or Electricity Consumption method, Currency Demand approach and the Multiple Indicators and Multiple Causes (MIMIC)) model. Vuletin (2008) estimated the informal economy of Mexico to be 28 percent of GDP using the MIMIC approach. Although some of the disaggregated GDP values of the states of Mexico have large residual errors, the power of the mean strengthens the argument that the informal/remittance economy of Mexico is larger than the official statistics.

The model developed to estimate the spatially disaggregate Gross State Incomes of the U.S. states ($EGSI_{US_i}$) demonstrates that the model, in general, 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 in the

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anomalous darkness of New York and California in the U.S. and of Mexico City in the Mexican Republic. Thus, while it was assumed that estimated urban population from spatial patterns of light can serve as a proxy measure of economic activity, it was observed through the analysis that, in the case of densely populated states with high levels of economic development, 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.

Because of the anomalous darkness of Mexico City relative to its level of economic development and population numbers, it has an outlier effect and is not shown in figure 4.11. Figure 4.11 demonstrates how well the modeled $EGSI_{Mex_i}$ is associated with the official GSP_{Mex_i} along with a 1:1 line. Except for Mexico City, the official GSP_{Mex_i} plotted against $EGSI_{Mex_i}$ shows a strong association with a Pearson's correlation coefficient of 0.87. Mexico City, being a primate city and the most important economic hub in the Mexican Republic, produces 21.8 percent of the country's GDP (INEGI 2000b). The city's GDP per capita is the highest of any city in Latin America (Consejo Nacional de Poblacion 2000). Although Mexico City has high levels of economic development, the $EGSI$ of Mexico City from the nighttime lights image is underestimated by 86 percent in comparison to the official GSP value. The inclusion of Mexico City lowers the correlation coefficient between the official GSP_{Mex_i} and modeled $EGSI_{Mex_i}$ values. Therefore, Mexico City is not shown in figure 4.11 but is included in the

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calculation of the Estimated Gross Domestic Income for Mexico ($EGDI_{Mex}$) and in the final computation of the underestimation of informal economy and remittances in the official statistic of GNI of Mexico (GNI_{Mex}).

The existing indirect approaches for estimating informal economy, e.g., the Currency Demand Approach, the Physical Input (Electricity Consumption Method) and the Multiple Causes and Multiple Indicators (MIMIC) model rely on multiple official, survey-based datasets (Schneider and Enste 2000; Vuletin 2008). This method, on the other hand, provides an independent estimate of economic statistics for Mexico. This independent method of estimating economic activity would help to overcome the shortcomings in the collection of official data. Results derived from this analysis using the spatial pattern of lights on the DMSP-OLS satellite-derived data provide an objective estimate of economic activity. Moreover, it also provides 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.

Summary -

This chapter focused on developing a model for estimating the location and magnitude of GSP, informal economy and remittances for the upper middle income country of Mexico. The model was developed on the basis of the spatial patterns of nighttime satellite imagery and was trained by using the Adjusted Official Gross State Product ($AGSP_{US_i}$) for the U.S. states. The result obtained by subtracting the official GNI statistic of Mexico (GNI_{Mex}) from the estimated Gross Domestic Income ($EGDI_{Mex}$) suggested that

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the informal economy and inflow of remittances into Mexico may be approximately 50 percent larger than what is officially recorded in the published official *GNI* statistic of Mexico (GNI_{Mex}). This method although still in the 'exploratory' stage provides a simple and independent means for estimating and mapping economic activity, which assumes special significance in countries like Mexico where the informal economy is expanding after the economic restructuring following NAFTA.

The following chapter, chapter five, applies the same methods, that is, slope and intercept parameters derived from the regression models developed between spatial patterns of nighttime imagery and official Adjusted Gross State Product for the states of the U.S. to estimate the formal and informal economic activity for India.

CHAPTER 5

ESTIMATION OF INDIA'S INFORMAL ECONOMY AND REMITTANCES USING NIGHTTIME IMAGERY

5.1 Brief economic history of India – causes for the increase of informal economic activities in India -

India, after independence in 1947, had adopted a socialistic model of economic development, without any reliance on global markets, international trade and foreign direct investments (FDI). India started having balance of payments problems since 1985 and in 1990 the crisis reached to a point that India could just about finance three weeks' worth of imports. The Government of India headed by Narasimha Rao, under the directives of Dr. Manmohan Singh, the then Finance minister of India, ushered several reforms to liberalize the Indian economy in order to lift the country out of the economic crisis. The economic reforms encouraged private businesses to prosper by removing the requirement of license approval, encouraged FDI, and led to the privatization of public companies (Sachs 2005). While liberalization of the Indian economy has led to rapid economic growth, many of the benefits of globalization (that came about with the liberalization of the economy) have not reached the poor and vulnerable sections of the Indian population and most of this poor and vulnerable population is engaged in informal employment (Sengupta 2008). There has been an increase in informal employment in India for almost the same reasons as in Mexico. In the global economic system, in order to remain competitive and reap profits, companies have replaced permanent laborers

with part-time laborers and have started sub-contracting jobs to small scale units (which, are mostly informal) (Portes et al. 1989; Chen 2003). In fact, subcontracting and outsourcing are the principal means of linking informal economy with formal economy in the global economic system (Chen 2007). Also, developing countries have switched to the production of goods which are capital-intensive and require skilled-laborers. Thus, employment is being provided to the skilled and educated population but the unskilled, poor laborers have been left behind. These laborers are left with no other alternative but to support themselves through informal employment (Aguilar 1997). According to the National Sample Survey (NSS) 55th 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. Another major cause for the increase of informal employment in India has been the mass migration of population from the rural to the urban areas in search of work. 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). 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).

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

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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 (Sengupta 2008).

5.2 Defining Unorganized sector and Unorganized employment in India

In India the terms 'organized' and 'unorganized' are used for what is internationally known as 'formal' and 'informal'. NCEUS has defined the unorganized sector and unorganized or informal employment based on the broader definition of informal economy which was adopted in the 17th ICLS in 2003, which includes both the unregulated nature of employment and the characteristics of enterprises to describe informal economy. The definitions are 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) (Sengupta 2008).

5.3 Development of alternative measures of informal economy and remittances for India from the nighttime lights imagery -

Recognizing the problems associated with estimating the magnitude and spatial distribution of economic activity, the alternative method which was developed for estimating the values of economic activities in Mexico in the previous chapter using known relationships between the spatial patterns of nighttime satellite imagery and economic activity in the U.S., was also applied for India. To reiterate the method, a model was developed for estimating the Gross State Income *(GSI)* of the 48 contiguous states of the U.S. using the arguably more reliable statistics 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). 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* statistics, informal economy and remittances to estimate the contribution of the informal economy and remittances towards the *GNI* of India.

Methods -

5.4 Data used -

5.4.1 Radiance-calibrated nighttime satellite imagery data and LandScan population data –

The radiance-calibrated image of 2000-2001 (figure 5.1) which was used to develop the proxy measure of economic activity for Mexico and the LandScan population grid of 2000 (figure 5.2) which was used for estimating population of the demarcated urban areas

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for Mexico were applied similarly to estimate the urban population and subsequently the economic activity for India.
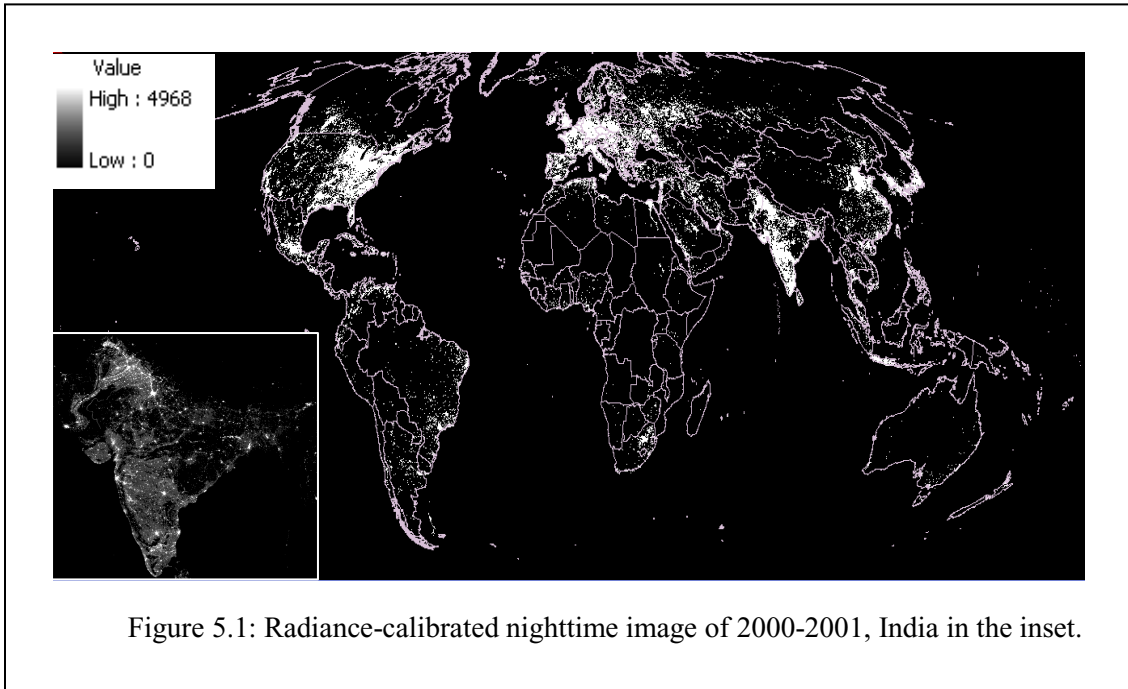

Figure 5.1: Radiance-calibrated nighttime image of 2000-2001, India in the inset.
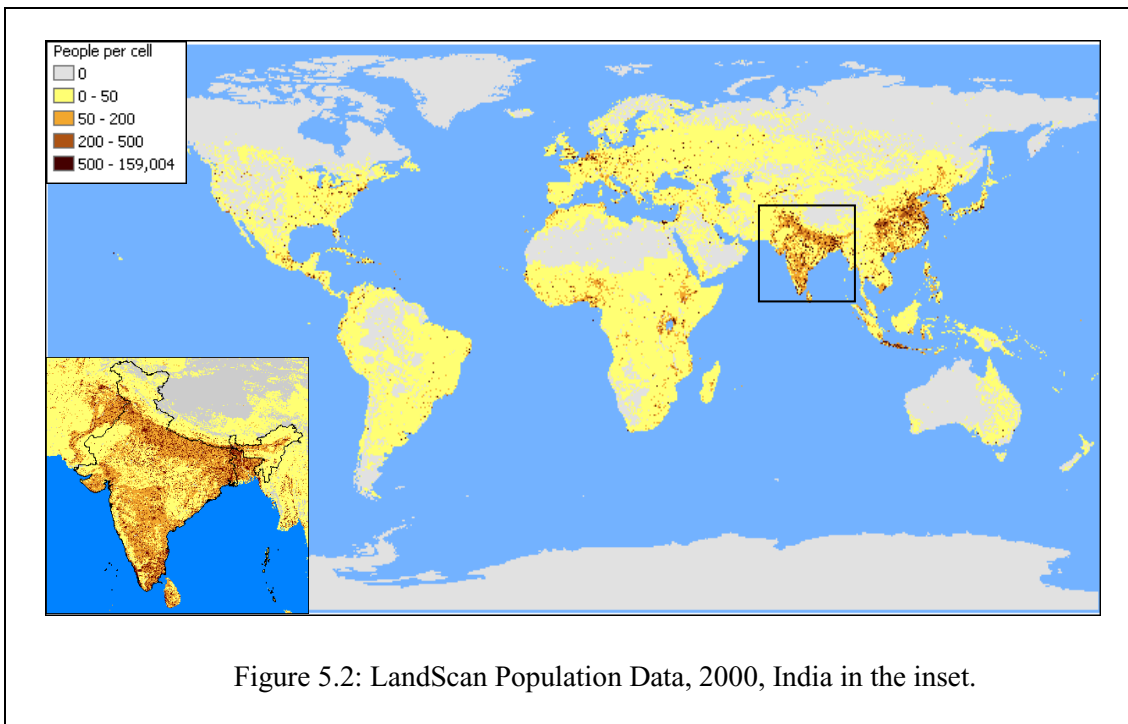
Figure 5.2: LandScan Population Data, 2000, India in the inset.

5.4.2 Official measures or statistics of the *GNI, GDP* and *GSP* data

The sources of *GNI, GDP,* and *GSP* data for the U.S. are the same as were discussed in the previous chapter, with Table 4.1 highlighting the inconsistencies between different *GDP* and *GNI* statistics for the U.S. that were derived from different sources and /or through the application of different computing methods. The inconsistencies for the data of India are shown in Table 5.1 with the *GDP* values ranging between U.S. $378 billion and Purchasing Power Parity (PPP) U.S. $2,474 billion.

GDP statistic of India for the year 2000 was obtained from the Central Statistical Organization (CSO 2000a). 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* value was converted into U.S. dollars on the basis of the official exchange rate for 2000 as well as the PPP conversion factor for 2000. The *GNI* statistic 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* statistics 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* statistic 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* statistics for each state/UT of India for the year 2000 were obtained from the CSO (CSO, 2000a). The *GSP* statistics which were in lakhs of Rupees were converted into PPP U.S. dollars by applying the PPP conversion factor (PPP U.S. $$GSP_{Ind_i}$) (Table 5.4, Column 2).

Table 5.1 Comparison of the *GNI* and *GDP* statistics of India from different sources

Row no.	Statistic	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 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

In spite of the discrepancies in reported economic indicators, the adjusted *GSP* statistics ($AGSP_{US_i}$) derived from the U.S. Bureau of Economic Analysis were assumed to be the most reliable official statistics 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). So, as in the case of Mexico, the subsequent analysis for India was also based on the $AGSP_{US_i}$ (Table 4.5, Column 2).

Also, since the PPP values are the standard used for international comparisons, the PPP U.S. $$GNI$ statistic of India (in bold in row 3 of Table 5.1) and the PPP U.S. $ GSP_{Ind_i} (Table 5.4) were used to facilitate comparison of results.

5.4.3 Official statistics of the informal economy and remittances of India –

In the National Accounts Statistics of India, statistics 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.

There exist several estimates of the contribution of informal economy towards *GDP*. According to a report for the United Nations Development Program (UNDP) (Anand 2001), about 63 percent of the value added to the overall *GDP* of the country can be attributed to the unorganized sector (when urban and rural areas are taken together). According to the estimates made by Schneider (2007) using the DYMIMIC (dynamic multiple-indicators multiple-causes) model, the contribution of informal economy towards *GDP* for India for the year 2005 was 25.1 percent.

For this paper, the statistic of the contribution of the informal economy to total *GDP* of India for the year 2000 was obtained from the Central Statistical Organization (CSO) of India (CSO 2000c). 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 (Table 5.2) This is equivalent to approximately 57 percent of India's *GDP* for 2000.

Table 5.2 Reported value of the informal economy statistic of India

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

Source: Central Statistical Organization, National Accounts Statistics

India is the largest remittance receiving country (Maimbo and Ratha 2005) and with the problems associated with the remittance flows going unrecorded in the national accounts, it can be expected that a lot of data on remittances go unrecorded and therefore underestimated in the national accounts of India. The statistic 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 PPP US $13 billion, approximately 0.6 percent of India's *GNI* for 2000.

5.5 Data analysis –

The methods which were developed to estimate the formal and informal economic activity for Mexico were applied for estimating the economic activity of India. The models were also based on the same four assumptions which were made for Mexico. An overview of the various stages of the model is provided. 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 5.3). 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 5.3, P'_{US_i} in Table 5.3). In the next step (Stage 2 in figure 5.3), a multiple regression model was developed to estimate Gross State Income of the U.S. states ($EGSI_{US_i}$ in Table 5.3) 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 5.3), and (3) adjusted *GSP* of each U.S. state ($AGSP_{US_i}$ in Table

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5.3). Next (Stage 3 in figure 5.3), 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 5.3). 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 5.3). 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 5.3, $EGSI_{Ind_i}$ in Table 5.3). $EGSI_{Ind_i}$ 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 5.3, $AEGDI_{Ind}$ in Table 5.3). The underestimation of the informal economy and remittances in the official GNI statistic (GNI_{Ind} in Table 5.3) was calculated by subtracting the GNI_{Ind} from the $AEGDI_{Ind}$ (Stage 6 in figure 5.3, $UIER$ in Table 5.3). Definitions and abbreviations for all the economic variables which were developed and used in different stages of the analysis are presented in Table 5.3.

Table 5.3 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 U.S. state (i), demarcated by the brightness threshold
P'_{US_i}	Estimated urban population for each U.S. state (i) demarcated by the brightness threshold
S_{US_i}	Sum of lights of the lit areas for each U.S. state *(i)*
$AGSP_{US_i}$	Adjusted Official Gross State Product for each U.S. 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 U.S. state *(i)*; sum of the formal economy, informal economy and remittances as estimated from the nighttime lights image
Residual$_{USi}$	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 U.S. 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*

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Figure 5.3: Overview of the model to predict the underestimation of informal
economy and remittances in India's official *GNI* statistic.
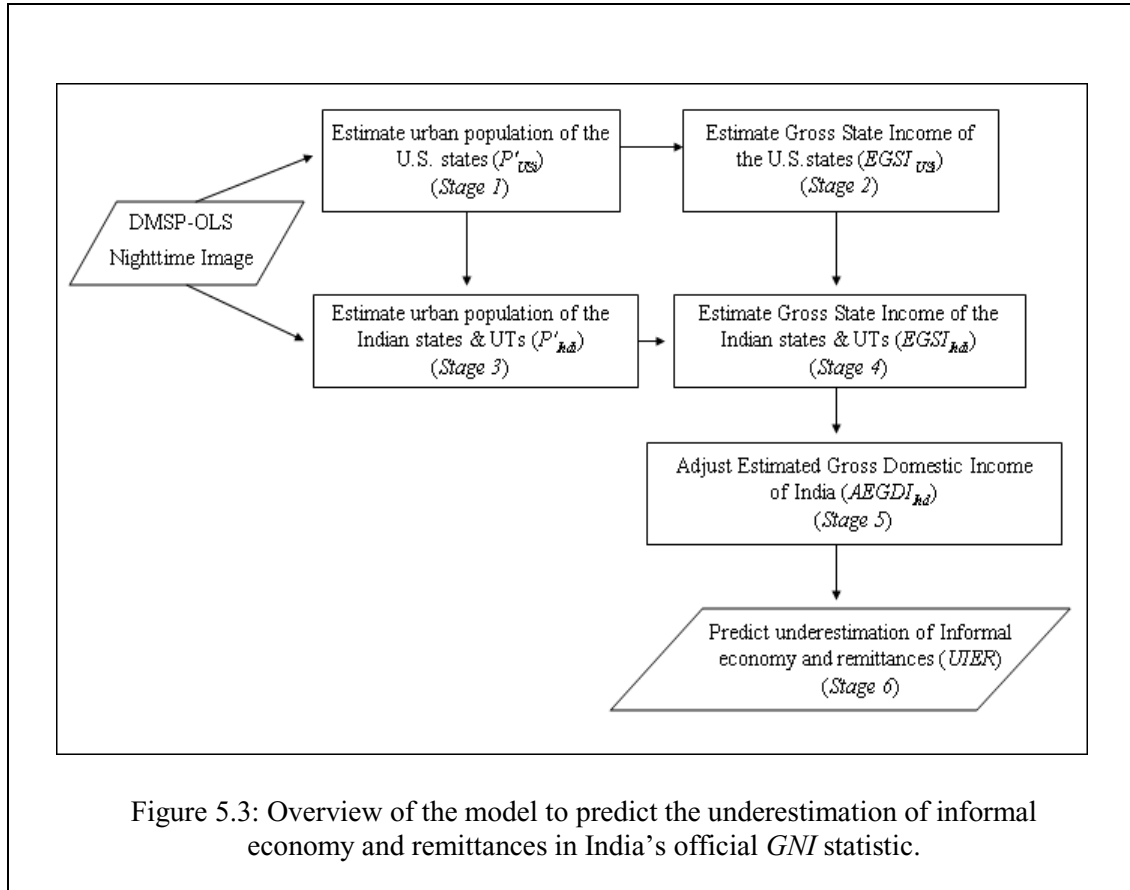
Since the first and second stages (figures 4.4 and 4.6) of the model are identical to the

model developed for Mexico, they are not discussed in details in this chapter again. In the

first stage, estimated urban population of the 48 contiguous U.S. states (P'_{US_i}), was

determined. Also, the corresponding regression model parameters α_{1US} and β_{1US} (5.10

and 1.07, respectively) which were used to estimate the urban population of the states and

UTs of India were also derived. In the second stage of the model, the Estimated Gross

State Income ($EGSI_{US_i}$) for each U.S. state was derived through a multiple regression

model and the model also provided the regression parameters α_{2US}, β_{2US}, and

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β_{3US} (16.11, 0.62, and 2.1 x 10^{-7}, respectively) for estimating the Gross State Income for

the states and UTs of India.

5.5.1 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 5.4).

Figure 5.4. 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.
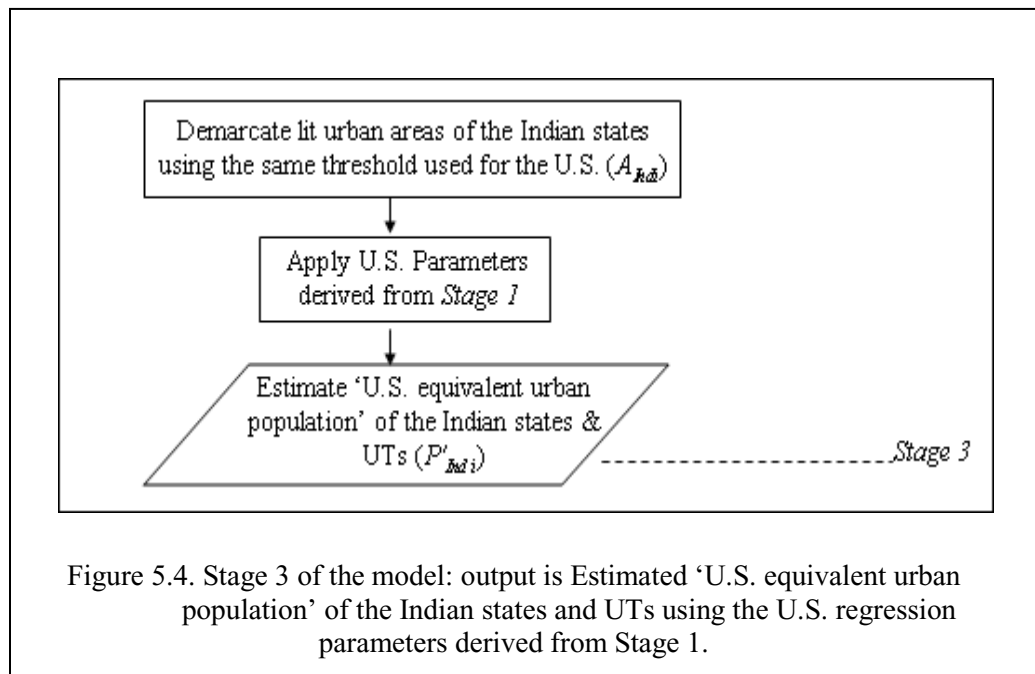
The same U.S. brightness threshold was used to delineate the lit urban areas of India

in order to apply the parameters that were estimated for the U.S. and to conform to the

assumption that economic activity creates the same spatial patterns of light in the U.S.

and in India. Figure 5.5 shows how well the U.S. brightness threshold demarcates the

four largest metropolitan cities in India and the urban areas surrounding them.

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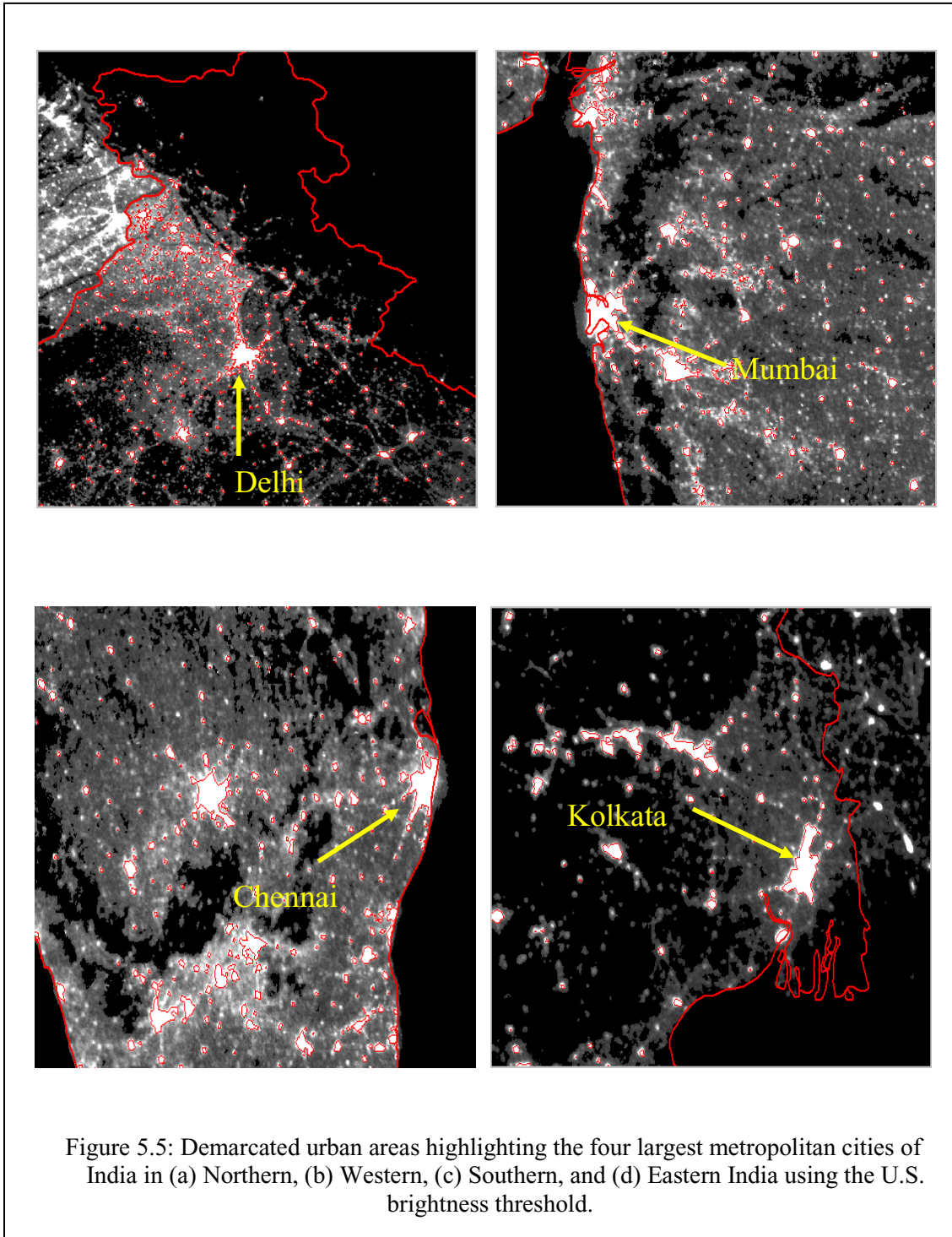
Figure 5.5: Demarcated urban areas highlighting the four largest metropolitan cities of India in (a) Northern, (b) Western, (c) Southern, and (d) Eastern India using the U.S. brightness threshold.

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 5.1).

$$P'_{Ind_i} = \exp(\alpha_{1US} + \beta_{1US} \times \ln(A_{Ind_i})) \qquad (5.1)$$

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

In Stage 4 (figure 5.6), 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 5.2).

$$EGSI_{Ind_i} = \exp(\alpha_{2US} + \beta_{2US} \times \ln(P'_{Ind_i}) + \beta_{3US} \times S_{Ind_i}) \qquad (5.2)$$

Figure 5.6: 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.
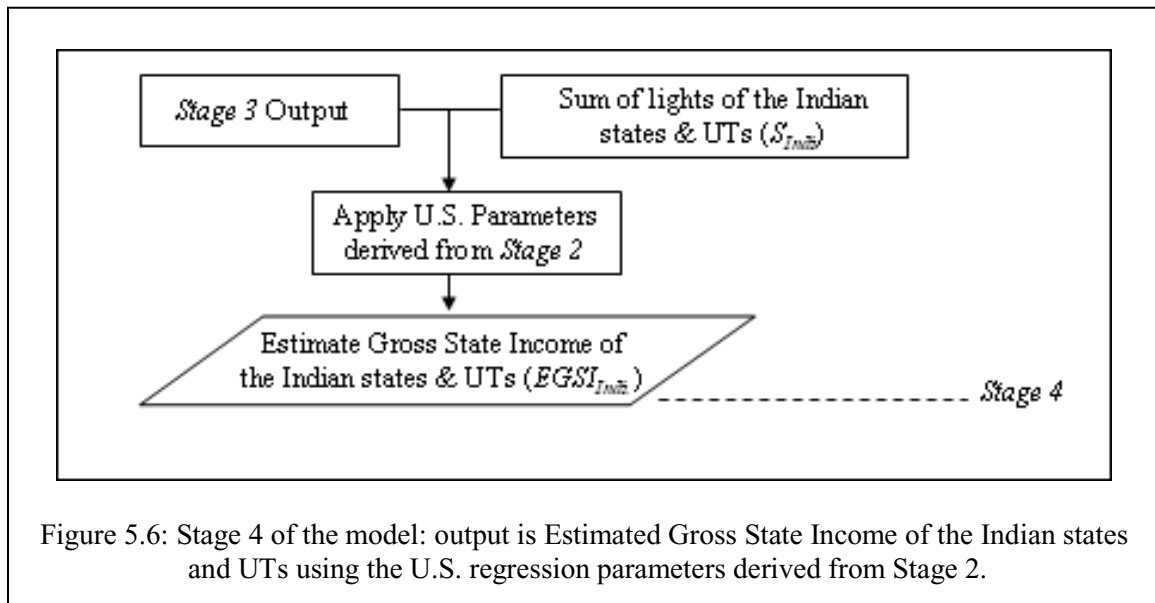
$EGSI_{Ind_i}$ of each Indian state/UT derived from the DMSP-OLS image was assumed to include the formal economy, informal economy, and the estimates of the remittance inflow into India. $EGSI_{Ind_i}$ should therefore be compared to the official GNI statistic; however GNI values are not available at 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, it was concluded that the $EGSI_{Ind_i}$ (which was 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 5.7), indicating that $EGSI_{Ind_i}$ was slightly overestimated for seven Indian states/UTs and was underestimated for the rest. The correlation coefficient

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(Pearson's r) of the official GSP_{Ind_i} versus $EGSI_{Ind_i}$ is 0.93, indicating a strong

association between the two variables.
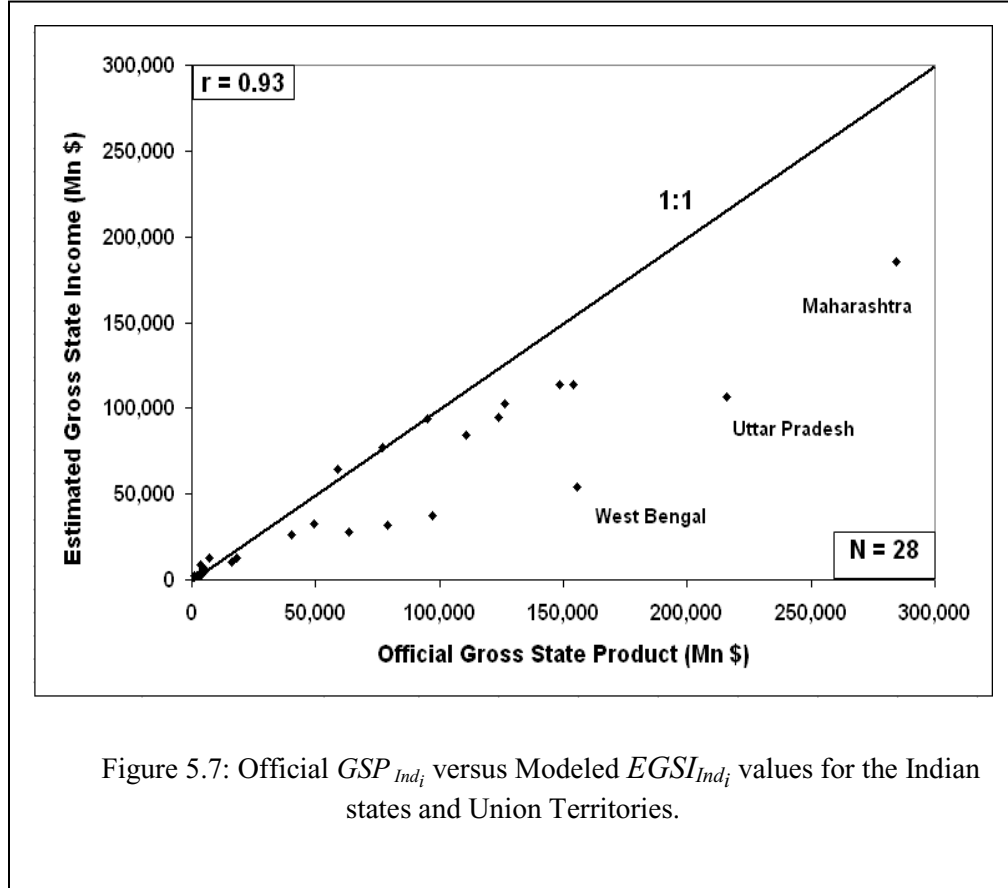
Figure 5.7: Official GSP_{Ind_i} versus Modeled $EGSI_{Ind_i}$ values for the Indian
states and Union Territories.

5.5.3 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* statistic of India (GNI_{Ind}). Both $EGDI_{Ind}$

and GNI_{Ind} include the formal economy, informal economy and the inflow of remittances

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into the economy. It was 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}). Then $EGDI_{Ind}$ was multiplied by the ratio, resulting in the Adjusted Estimated Gross Domestic Income of India ($AEGDI_{Ind}$) (Stage 5, figure 5.8).

Figure 5.8: Stage 5 of the model: output is increased value of Estimated Gross Domestic Income for all of India.
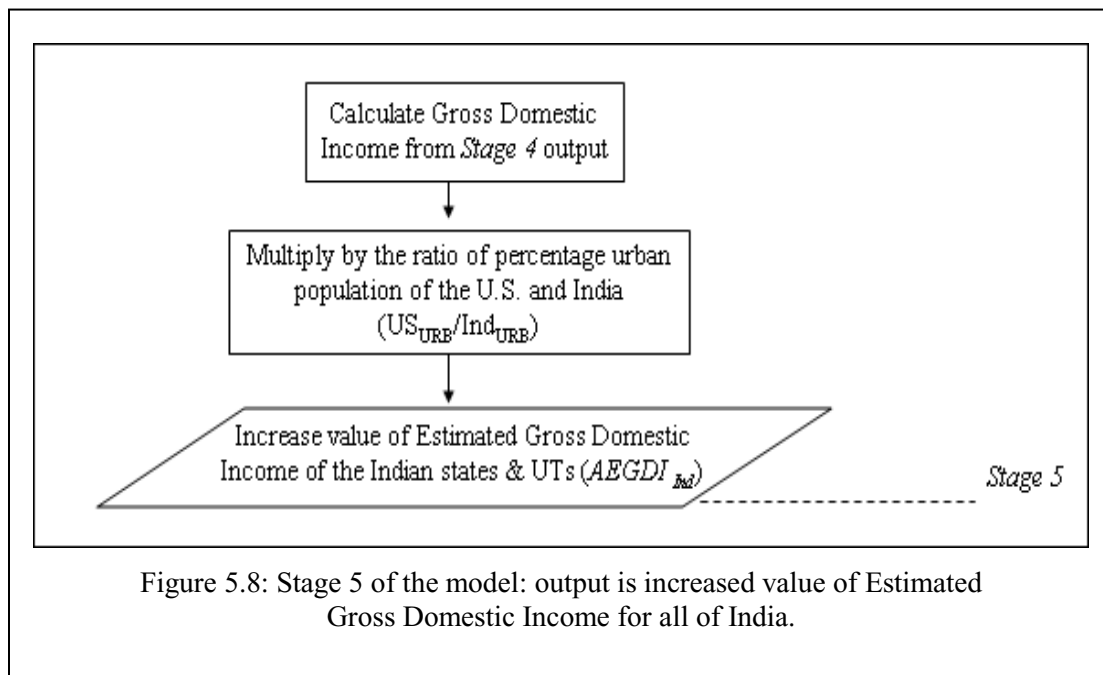
In the final stage, the magnitude of the informal economy and remittances was estimated (Stage 6, figure 5.9). The $AEGDI_{Ind}$ was subtracted from the official GNI_{Ind}, and this gave the predicted underestimation of informal economy and remittances *(UIER)* in the official statistics (Equation 5.3).

$$UIER = AEGDI_{Ind} - GNI_{Ind} \tag{5.3}$$

Figure 5.9: Stage 6 of the model: output is predicted underestimation of informal economy and remittances in the official *GNI* statistic of India.
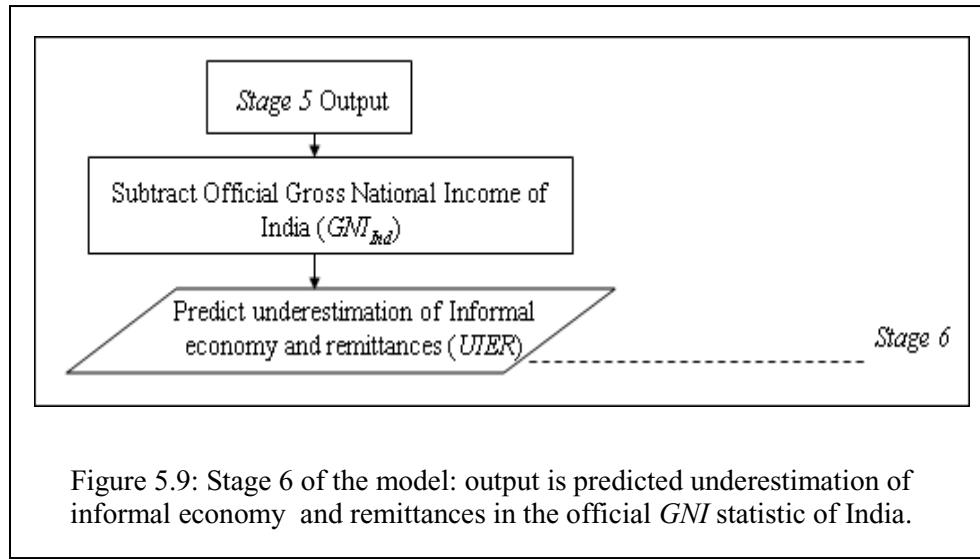
5.6 Results –

The relationship between the official *AGSP* and modeled *EGSI* for the U.S. has been discussed and mapped in the previous chapter (Table 4.5 and figure 4.13). The residuals were calculated by using the formula (Equation 5.4) –

$$\text{Residual}_{US_i} = \frac{AGSP_{US_i} - EGSI_{US_i}}{AGSP_{US_i}} \times 100 \tag{5.4}$$

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5.6.1 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 5.4, figure 5.10). 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.

Table 5.4 Official GSP_{Ind_i}, Modeled $EGSI_{Ind_i}$, and Percentage Residual for each Indian state and Union Territory

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

Figure 5.10: Percentage Residual Gross State Product Map of the states and Union Territories of India.

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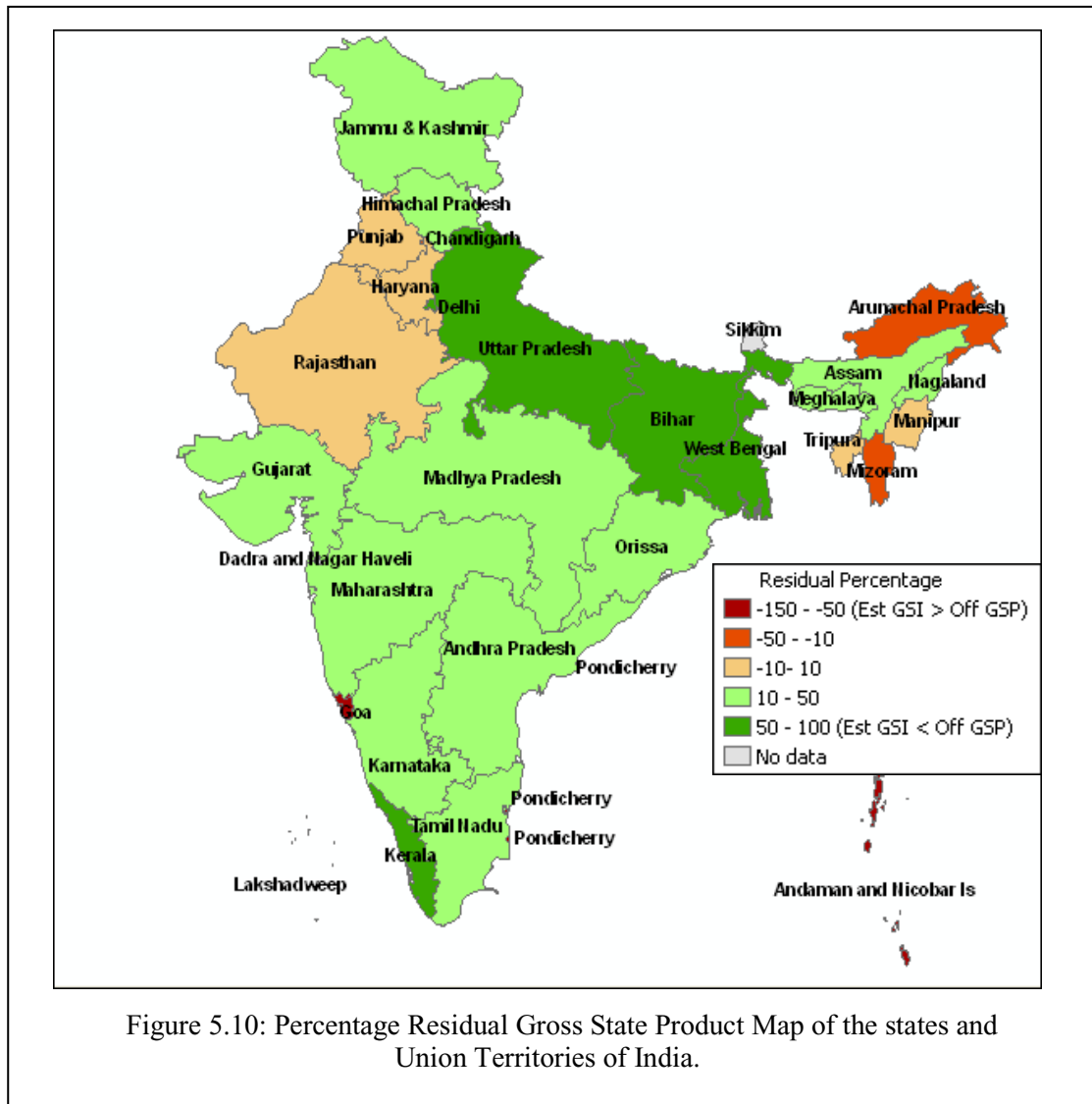
5.6.2 Estimating the magnitude of underestimation of informal economy and remittances in the official statistics of *GNI*, informal economy and remittances of India

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 5.5). 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, 2000b) (Row 3 of Table 5.5). 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 5.5). Subtracting the GNI_{Ind} from $AEGDI_{Ind}$ gave the predicted underestimation of informal economy and remittances in the official statistics (Row 4 of Table 5.5). In order to derive the magnitude of underestimation the official statistics of informal economy and remittances for the year 2000 were summed (Row 7 of Table 5.5). Then, the predicted value of informal economy and remittances (Row 8 of Table 5.5) was divided by the sum of the official measures of informal economy and remittances (Row 9 of Table 5.5). The result demonstrated that the informal economy and the inflow of remittances for India was about 50 percent larger than what was recorded in the official statistics of Gross National Income (GNI_{Ind}).

Table 5.5 Determining the magnitude of underestimation of informal economy and remittances in the official statistic 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 statistic 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 statistic of Informal economy in 2000 ▲	1,115
6	Official statistic of remittances in 2000 #	13
7	Total official statistic of informal economy and remittances	1,128
8	Predicted underestimation of remittances and informal economy	1,736
9	Total official statistic of informal economy and remittances	1,128
10	Magnitude of underestimation	~ 50%

* 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

5.7 Discussion -

The radiance-calibrated nighttime image of 2000-2001 and the *AGSP$_{US_i}$* of each U.S. state were used to develop a regression model for estimating *EGSI$_{Ind_i}$* for each of the Indian states/UTs. The *AEGDI$_{Ind}$* was compared to the "official" value of *GNI$_{Ind}$*. When this model was applied to Mexico in the previous chapter, 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 of Mexico provided the predicted underestimation of informal

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economy and remittances in the official statistics (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}) for each of the Indian states/UTs of India (figure 5.7); 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 may have been 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 have been about 50 percent larger than what was recorded in the official statistic of *GNI* of India. It is interesting to note that informal economy and inflow of remittances for Mexico was also estimated to be 50 percent larger than what was recorded in the official *GNI* value, albeit without any adjustments. 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.

It was observed that as in the case of New York and California in the U.S., and Mexico City in the Mexican Republic (Ghosh et al. 2009), the model underestimated the Gross State Incomes (*GSI*) of the Indian states, Maharashtra and West Bengal, which had high official values of Gross State Product (*GSP*), relative to their population or relative

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to lit area. Therefore, the argument which was made in the previous chapter that although spatial patterns of lights serve as a proxy measure of population, and subsequently of wealth, it actually tends to underestimate population and economic activity in the states that are densely populated was confirmed again in the case of India. Nevertheless, as for Mexico, this method provides an independent estimate of economic activity for India without using any population or economic data recorded for India.

Summary –

In this chapter the methodology which was employed to estimate the economic activity of Mexico in the previous chapter was used to estimate the location and magnitude of *GSP, GDP*, the informal economy and remittances for the lower-income country of India (World Bank 2002). The model was developed on the basis of the spatial patterns of nighttime satellite imagery and was 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 and then subtracting it from the official *GNI s*tatistic (GNI_{Ind}) suggested 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 50 percent larger than what was officially recorded in the published official statistic of *GNI* of India. This method, although in the 'exploratory' stage, provides an innovative technique of estimating the formal and informal economic activities of countries independently.

CHAPTER 6

SHEDDING LIGHT ON THE GLOBAL DISTRIBUTION OF ECONOMIC ACTIVITY

This chapter deals with creating a disaggregated map of Gross Domestic Product (*GDP*) and Gross State Product (*GSP*). The background discussions for this chapter regarding the problems associated with collection and mapping of *GDP* or *GSP* data, the usefulness of the nighttime lights as a proxy measure of economic activity, and the studies pertaining to the estimation of economic activity using nighttime lights have already been done in chapter three.

However, to state briefly again, maps showing the distribution of wealth of countries in terms of *GDP* are usually available at the national level and occasionally at the sub-national level. This prevents the integration of economic data with other physical and environmental data, which are usually available in raster or grid formats. Thus, a disaggregated map of economic activity would facilitate easy integration of economic data with other physical and environmental data, and would also allow immense analytical flexibility by allowing integration to different units of analysis.

Doll et al. (2000) created the first global disaggregated map of *GDP* at one degree resolution based upon a log-linear relationship between lit urban areas and official Purchasing Power Parity (PPP) *GDP* for 46 countries. Through their analysis they

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recognized that the use of radiance-calibrated nighttime lights data, as well as inclusion of the contributions from the agricultural, industrial, and service sectors, could provide much better results. Sutton and Costanza (2002) used the radiance-calibrated image of 1996-97 to create a 30 arc-second (one km^2) grid of global marketed economic activity. They did this based on simple, nationally specific ratios of *GDP* to light energy (LE) for each nation of the world and then applied it globally. Doll et al. (2006) again used the 1996-97 radiance-calibrated image to create estimated *GDP* maps of the U.S. and 11 European Union countries at 5 km resolution using linear relationships between total radiance and Gross Regional Product (*GRP*). Through their analysis, they also highlighted a number of potential areas for improvement and further investigation. They relied only on lights to distribute economic activity. Although this is a rational assumption for countries where industry and service sectors comprise 90 percent of the economy, the assumption may not be valid for countries where agriculture comprises a larger section of the national economy. Also, maps based only on lights do not consider the spatial distribution of agricultural productivity, but rather consider agricultural economic activity just as a node; that is, the resulting map locates agricultural productivity in the towns which emit light and not in the fields where crops are grown. In this chapter a global grid of total (formal plus informal) economic activity was generated from the nighttime lights data by building upon these previous attempts at creating grids of economic activity, while also forging to address the drawbacks of the previous studies. Specifically, the goal of the current study was to generate a unique relationship between lights within an administrative unit (states of China, India, Mexico, and the U.S., and other countries of the world) and Gross State Product (*GSP*) or Gross Domestic Product

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(*GDP*) of that unit. This was initially based on log-linear relationship between the sum of light intensity values and official *GSP* or *GDP* values, which has been exploited in a number of previous studies. Through further analysis, unique coefficients (β_i') were derived for each administrative unit. These unique coefficients were multiplied by the sum of lights of the associated unit to estimate total economic activity for that administrative unit (Equations 6.1 and 6.2). Because it was assumed that when the sum of lights equals zero, *GSP* or *GDP* also equals zero, the relationship was represented as follows:

$$\beta_i' \text{ x } SL_i = GSPI_i \tag{6.1}$$

$$\beta_i' \text{ x } SL_i = GDPI_i \tag{6.2}$$

where, SL_i is the sum of lights of each administrative unit i; β_i' is the estimated unique coefficient for each administrative unit i; $GSPI_i$ is the total estimated (formal plus informal) economic activity for each state of China, India, Mexico, and the U.S.; $GDPI_i$ is the total estimated (formal plus informal) economic activity for each country i. The estimated $GSPI_i$ and $GDPI_i$ values were spatially distributed within each administrative unit using the percentage contribution of agriculture towards *GDP* for each country, combined with raster representations of the nighttime lights image and the LandScan population grid. Specifically, the percentage of total estimated economic activity attributed to agriculture was spatially distributed according to the LandScan population grid, and the percentage of economic activity attributed to commercial/industrial sectors was distributed according to the nighttime lights imagery.

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Methods –

6.1 Data used –

6.1.1 Nighttime lights imagery –

The nighttime lights image was used to calculate the sum of light intensity values for each administrative unit and to distribute the percentage of total estimated economic activity not attributed to agriculture (in other words, attributed to commercial/industrial activity) for each administrative unit. A merged stable lights and radiance-calibrated nighttime image of 2006 was used to estimate total economic activity of each administrative unit. The 2006 stable lights data were composited from a set of cloud-free orbits for the year 2006, with the ephemeral light sources, such as fires and lightning removed (Elvidge et al. 2009a). The main problem associated with the DMSP stable lights data is the saturation of data in city centers and other brightly lit zones. The radiance-calibrated image of 2006 was produced by combining three images collected at three different fixed gain settings. The radiance-calibrated image helps to overcome the problem of saturation of city centers and provides a much better image of the internal structure of cities by highlighting spatial detail associated with brightness variations within urban centers (Elvidge et al. 1999). Blending the stable lights data and the combined radiance-calibrated image made it possible to accommodate the best features of both types of nighttime images.

The spatial resolution of the original nighttime lights data is 2.7 km. The images are geolocated to 30 arc-second grids, equivalent to approximately one km^2 at the equator. The latitudinal extent of the dataset is from 75˚N to 65˚S and the longitudinal extent is from 180˚W to180˚E (figure 6.1).

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Figure 6.1: Merged stable lights and radiance-calibrated image of 2006.

6.1.2 LandScan population grid –

The LandScan population grid of 2006 was used to distribute the percentage of total

economic activity contributed by agriculture for each administrative unit. The U.S.

Department of Energy at Oak Ridge National Laboratory has produced a progressive

series of spatially disaggregated global population count datasets. The LandScan model

uses spatial data and image analysis techniques, along with multi-variable dasymetric

modeling approach, to apportion sub-national level census counts to each grid cell based

on proximity to roads, slope, land cover, and other information, within an administrative

boundary. The cells have integer population counts representing ambient population

distribution, that is, a population estimation that takes into account the movement of

people for work or travel and not only where people sleep. The dataset has a spatial

resolution of 30 arc-seconds (LandScan 2006). For this analysis, the northern latitudinal

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extent of the LandScan data was cropped to 75˚N (originally extends to 84˚N) and the southern latitudinal extent was cropped to 65˚S (originally extends to 90˚S) to match with the latitudinal extent of the nighttime lights data (figure 6.2).
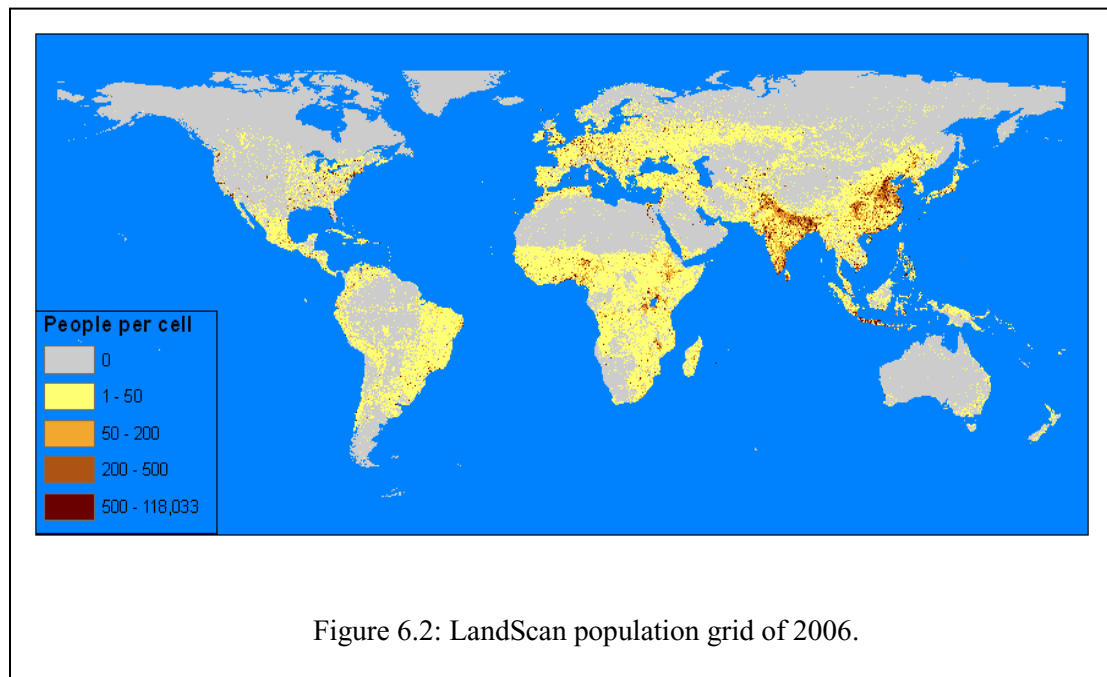

Figure 6.2: LandScan population grid of 2006.

6.1.3 Official Gross Domestic Product (*GDP*) and Gross State Product (*GSP*) data –

Official *GDP* and *GSP* data for each respective administrative unit, with added informal economy estimates, were used to calibrate the sum of lights to predict total economic activity through regression models for groups of administrative units. Official *GDP* data were obtained from the 2008 World Development Indicators for all available countries (World Bank 2008a). For most of the countries, the data were for the year 2006, but for a few countries 2006 data were not available, and 2005 *GDP* data were used. Data for a few of the countries were not available from the World Development Indicators, and

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for those countries, data were taken from the Central Intelligence Agency (CIA) World Factbook (CIA 2006). All official *GDP* data were expressed in Purchasing Power Parity (PPP) U.S. dollars. The PPP figure makes international comparisons possible, as it attempts to address the fluctuations in country exchange rates by expressing the quantity of goods and services each currency can buy locally as one dollar would buy in the U.S. (World Bank 1994).

The Gross State Product (*GSP*, i.e., *GDP* at the state level) of the U.S., Mexico, China, and India, were obtained from the statistical organizations of the respective countries. For the U.S., data were obtained from the U.S. Bureau of Economic Analysis (BEA 2006); for Mexico, from Instituto Nacional de Estadistica Geografia (INEGI 2006); for the provinces, municipalities, autonomous regions, and Special Administrative Regions of China, from the National Bureau of Statistics of China (National Bureau of Statistics of China 2006); and for India, from the Central Statistical Organization (CSO 2006). All the data were for the year 2006 and were converted into PPP U.S. dollars by using the PPP conversion factors for that year.

6.1.4 Informal economy data –

The informal economy is present in both the developed and developing countries (ILO 2002). Almost no official national *GDP* statistics take into account the contribution of informal economy. Different direct and indirect approaches for estimating the contribution of informal economy towards *GDP* exist. The dynamic multiple-indicators multiple-causes model (DYMIMIC) developed by Schneider (2007) is different from all the other approaches because it considers multiple causes leading to the existence and

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growth of informal economy, as well as multiple effects of the informal economy over time. In this model, the hidden economy is estimated as an unobserved variable over time through a factor-analytic approach. The three main causes of informal economy as distinguished by the model are as follows: high taxation, heavy regulation and declining "tax morality" (i.e., citizen's attitude towards the state). According to the model, the changes in the size of the informal economy are reflected by the following indicators: (a) monetary indicators – if activities in the informal economy rise, additional monetary transactions are required; (b) labor market indicators – increased participation of workers in the hidden sector would result in decreased participation in the official economy; and lastly, (c) production market indicators - when there is an increase of informal economy activity, inputs (especially labor) move out from the official economy and this displacement can have an overall depressing effect on the official growth of the economy (Schneider 2002).

Schneider (2007) used the DYMIMIC model to estimate the informal economy (which he calls the shadow economy) as a percentage of "official" *GDP* for 145 countries, including developing, transition, and highly developed Organization for Economic Co-operation and Development (OECD) economies, over the period between 1999 and 2005. He provided revised estimates for 21 OECD countries over the period between 1989 and 2009 (Schneider 2009a) and 25 transition countries over the period between 1999 and 2007 (Schneider 2009b). Thus, 2005 percentage estimates of the informal economy were available for the 96 developing countries, and 2006 percentage estimates were available for the 21 OECD and 25 transition countries. In the present study, the percentage informal economy estimates were added to the *GDP* of each

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country ($GDPS_i$) to develop the regression model to calibrate the sum of lights. However, since state level estimates of informal economy were not available, the country level estimates of the percentage informal economy for China, India, Mexico, and the U.S. were added to the state GSP values ($GSPS_i$).

6.1.5 Percentage contribution of the agricultural sector -

Agriculture is an important component of economic activity, especially in many of the developing countries. The nighttime lights imagery does not account for the percentage of economic activity contributed by agriculture, as this percentage is distributed in the darker areas of the nighttime lights images (corresponding to non-urban land use). Thus, the percentage contribution of estimated total economic activity attributed to agriculture was spatially distributed according to the LandScan population grid based on the assumption that rural populations living in those dark areas contribute to economic activity (mainly through agricultural activities), although they are not captured in the nighttime lights image. Data on the percentage contribution of agriculture towards GDP at the national level was acquired from the World Development Report of 2008 (World Bank 2008b) and from the CIA World Factbook (CIA 2006). The percentage contribution of the agricultural sector towards GDP were not available at the state level, and therefore the country level percentages for the four countries (China, India, Mexico, and the U.S.) were used to estimate the contribution of the agricultural sector towards GSP for each state.

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6.2 Data Analysis –

The creation of the disaggregated map of total (formal plus informal) economic activity involved two distinct parts. In the first part, total economic activity for each administrative unit ($GSPI_i$ or $GDPI_i$) was estimated by multiplying the sum of lights (i.e., sum of brightness values of lights for all lit areas) of each administrative unit by a unique coefficient (Equations 6.1 and 6.2). The second part involved spatially distributing the estimated total economic activity ($GSPI_i$ and $GDPI_i$) of each administrative unit into one km^2 grid cells based on the percentage contribution of agriculture, the nighttime lights image, and the LandScan population grid.

6.2.1 Estimating total economic activity for administrative units ($GSPI_i$ and $GDPI_i$)

The steps involved in the first part of the analysis are shown in the flow diagram of figure 6.3.
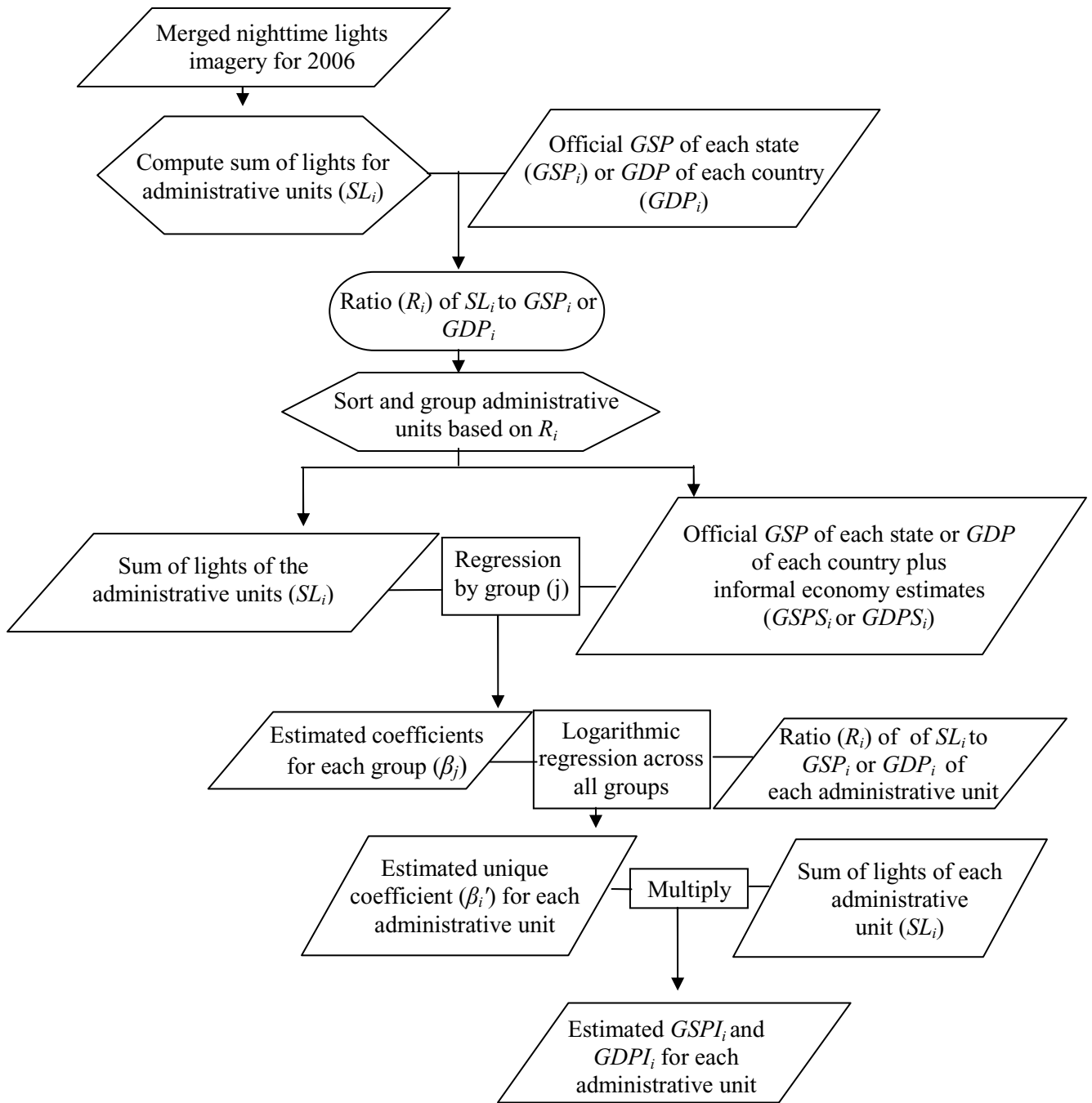
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Figure 6.3: Flow diagram showing the steps involved in estimating $GSPI_i$ for each of the states of China, India, Mexico, and the United States and $GDPI_i$ for each country.

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The first step towards estimating unique coefficients involved computing the sum of light intensity values within each of the administrative units (SL_i) from the merged nighttime lights image of 2006. The sum of lights was calculated at the sub-national level for China, India, Mexico, and the U.S. to reduce the influence of these 'outlier' countries, which have the greatest weight in increasing the R^2 value when the sum of lights is regressed against official GDP of all countries. Moreover, official GSP data were easily available for these four countries. Regression analysis between the sum of lights (SL_i) and official GDP_i or GSP_i value for each administrative unit was conducted, and it was observed that a given administrative unit may be brighter or dimmer in comparison to what was expected based on officially reported GSP_i or GDP_i values (i.e., fall above or below the best-fit regression line). As is seen in figure 6.4, countries such as Japan and Germany are much wealthier relative to their sum of lights value; on the other hand, Russia is much poorer relative to its sum of lights value. Also, this relationship provided only a moderately strong R^2 value of 0.73.

Figure 6.4: Relation between sum of lights (SL_i) and official GDP_i or GSP_i of the administrative units.
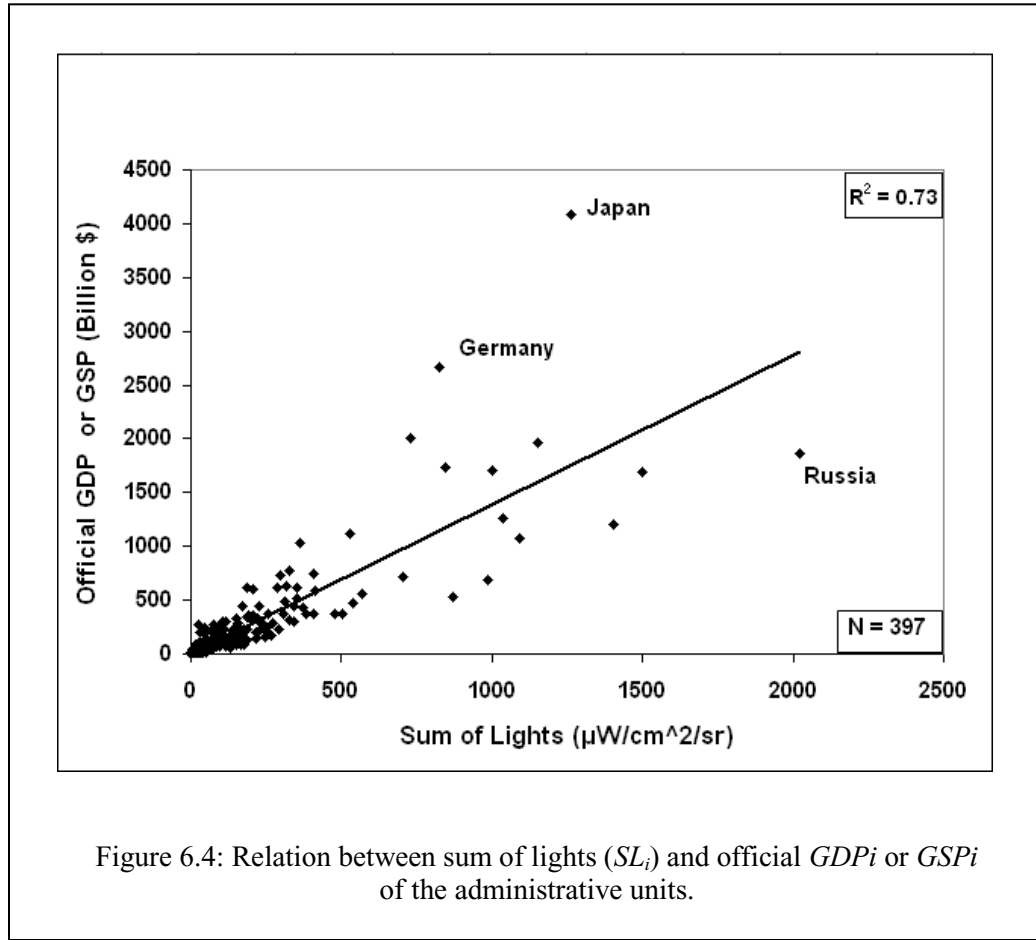
This observation indicated that better relationships between the sum of lights (SL_i) and GSP_i or GDP_i could be obtained if administrative units having similar ratios (R_i) between sum of lights (SL_i) and GSP_i or GDP_i were grouped together.

Next, ratios (R_i) of the sum of lights (SL_i) to the official GSP_i or GDP_i for each administrative unit were calculated as follows:

$$R_i = SL_i / GSP_i \qquad (6.3)$$

$$\text{or,} \qquad R_i = SL_i / GDP_i \qquad (6.4)$$

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The ratios helped to group the administrative units in terms of their relationship between official GSP_i or GDP_i and brightness values. The lower the ratio, the dimmer the administrative unit is relative to the level of economic development as measured from its official GSP_i or GDP_i statistics, and the higher the ratio, the brighter the administrative unit is relative to the level of economic development as measured from its official GSP_i or GDP_i statistics. Figure 6.5 (A), (B), and (C) present maps of the sum of lights (SL_i), GSP_i or GDP_i, and the ratio (R_i) of the administrative units.

After calculating the ratios (R_i), the administrative units were sorted in ascending order. There were 397 administrative units in all, and units were binned in groups of twenty with ten overlapping units in each subsequent group. This resulted in 36 groups of overlapping administrative units. Categorizing the administrative units based on these ratios helped to refine the coefficients for each group. Although administrative units in each group represented different levels of economic development, they fell within the specific range of lighting to GSP or GDP.

After grouping the administrative units based on the ratios (R_i), the sum of lights (SL_i) were calibrated to the official GSP_i or GDP_i with added informal economy estimates (i.e., $GSPS_i$ or $GDPS_i$) (Schneider 2007, 2009a, 2009b) through regression models for each of the 36 groups. The intercept was set to zero, based on the assumption that $GSPS_i$ or $GDPS_i$ should be zero when the sum of lights (SL_i) was zero. Coefficients of determination (R^2) greater than 0.9 was obtained for all 36 groups by modeling the SL_i as a linear function of $GSPS_i$ or $GDPS_i$.

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(A) Sum of lights (*SL*$_i$) in µW/cm^2/sr
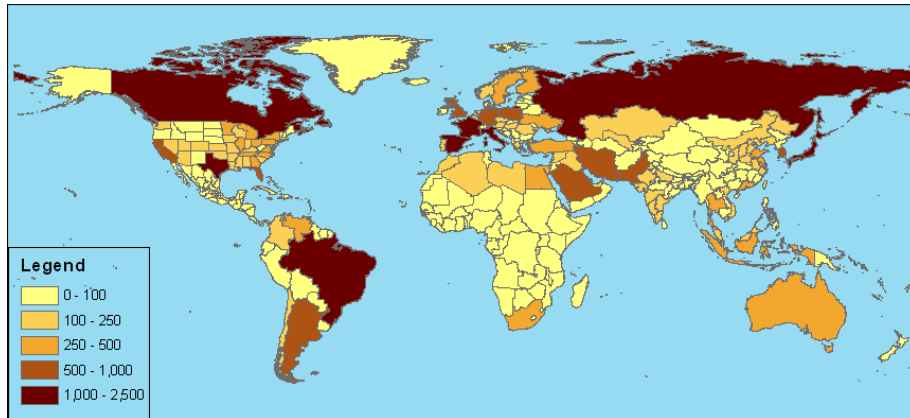
(B) Official *GSP*$_i$ or *GDP*$_i$ in billions of U.S. dollars
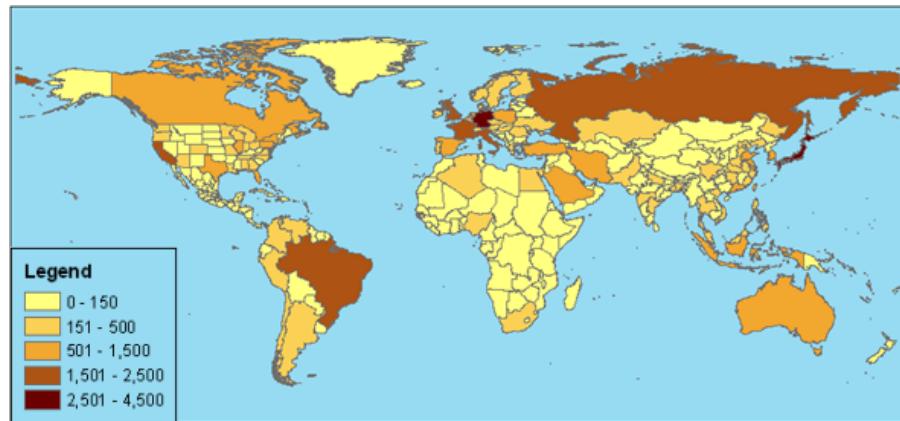
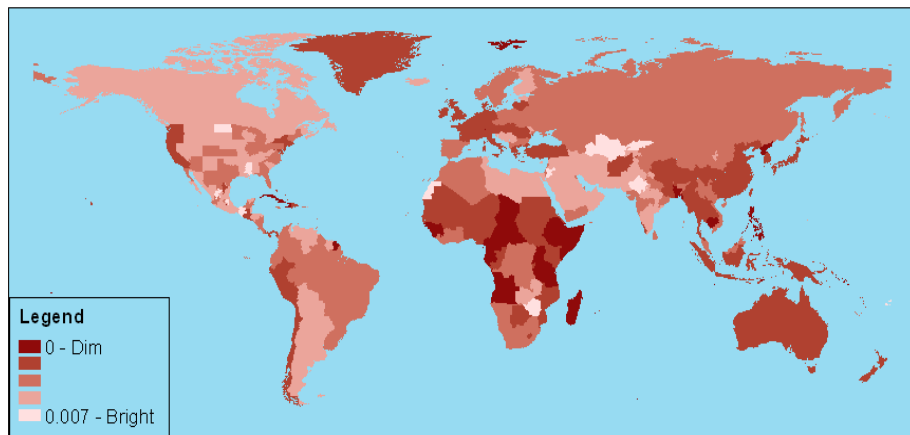

(C) Ratio of *SL*$_i$ to *GSP*$_i$ or *GDP*$_i$

Figure 6.5: (A) Sum of lights (*SL*$_i$), (B) Official *GSP*$_i$ or *GDP*$_i$,
(C) Ratio of *SL*$_i$ to *GDP*$_i$ or *GSP*$_i$.of the administrative units.

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The regression models provided beta coefficients (β_j) for each group (where j refers to the group index). Figure 6.6 shows a subset of the regression models for the groups of administrative units, where the first group has the lowest R_i values, and the thirty-sixth group has the highest R_i values.

Next, through experimentation of relationships between the different variables, an empirical relationship was observed between the ratios (R_i) of each administrative unit and the estimated coefficients (β_j) across all groups. For each successive group, the ratios of the overlapping last 10 administrative units and the coefficient value of the group in which the overlapping administrative units fell were used to depict the relationship. This relationship is described by a natural logarithmic function between these two variables (Equation 6.5). Exponentiating ln (β_j) provided unique coefficients for each of the administrative units (β_i') (Equation 6.6).

$$\ln (\beta_j) = 0.65 - 0.94 * \ln (R_i) \qquad (6.5)$$

$$\beta_i' = \mathrm{Exp} (0.65 - 0.94 * \ln (R_i)) \qquad (6.6)$$

There were a few outliers in the observed logarithmic relationship. The outliers which were dimmer than expected can be grouped into three categories as follows: (a) Small islands, such as, Solomon Islands, Maldives, and Bermuda; (b) extremely underdeveloped countries such as North Korea, Equatorial Guinea, Chad, Madagascar, Rwanda; and (c) city states, such as Hong Kong, District of Columbia. Each of these administrative units fell in the same group when they were categorized according to their ratios (R_i). The only outlier that was much brighter relative to its official GDP_i value was

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Zimbabwe. Outliers were excluded (leaving a total of 344 administrative units) when the logarithmic model was developed, but the resulting log-log regression model was used to estimate the unique coefficients for the outlier administrative units too. The logarithmic regression graph is shown in figure 6.7.

First group

Thirteenth group

Twenty-fifth group

Thirty-sixth group
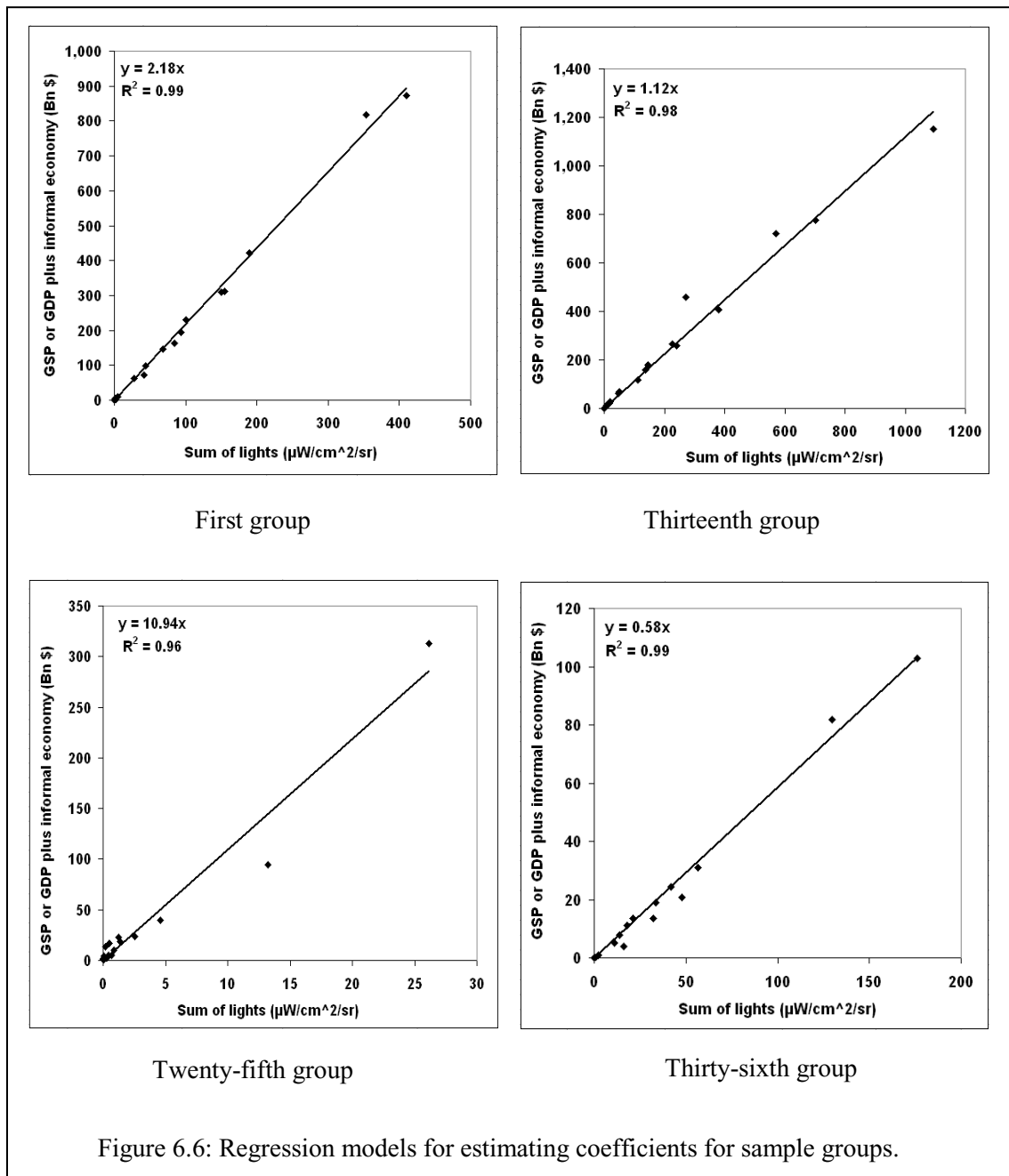
Figure 6.6: Regression models for estimating coefficients for sample groups.

Figure 6.7: The logarithmic regression to derive estimated unique coefficients,
where R_i = ratio of sum of lights to *GSP* or *GDP* and
β_j = Estimated group coefficient.
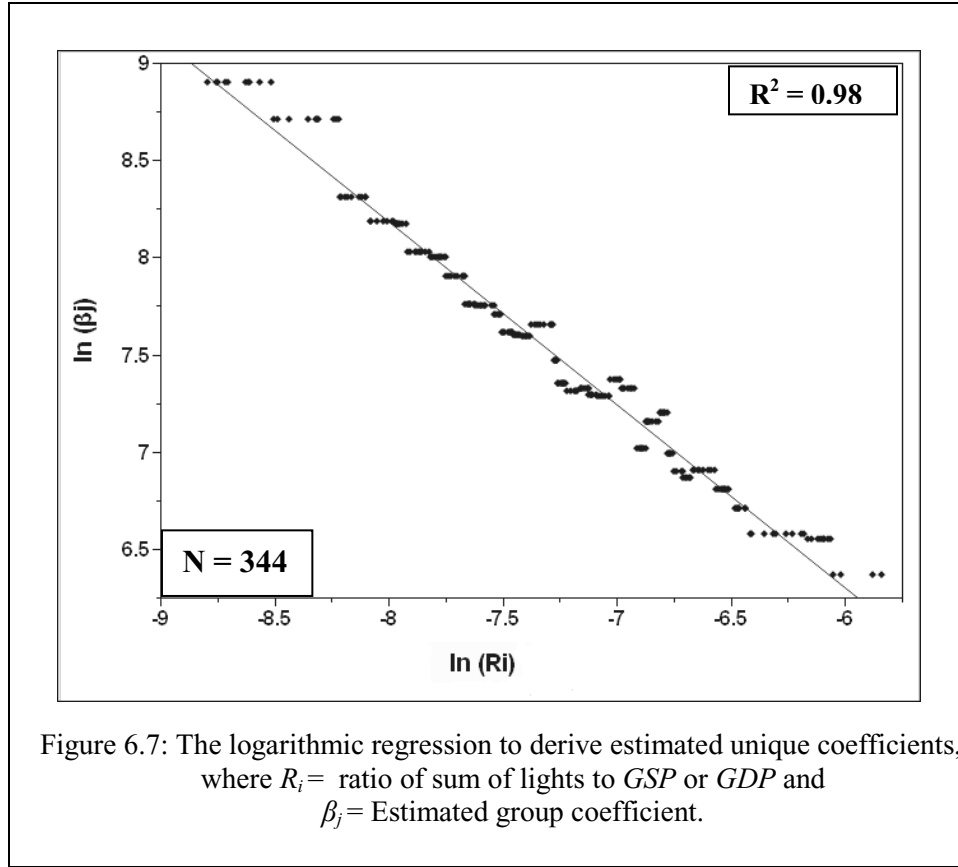
After the derivation of the estimated unique coefficient for each administrative unit

($\beta_i{}'$), the total economic activity (*GSPI$_i$* and *GDPI$_i$*), for each administrative unit was

estimated by multiplying the sum of lights of each administrative unit (*SL$_i$*) by its unique

coefficient ($\beta_i{}'$)   (Equations 6.1 and 6.2). The estimated *GSPI$_i$* or *GDPI$_i$* includes both the

formal and informal economies, and these values are represented in figure 6.8.

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Figure 6.8: Estimated $GSPI_i$ for the states of China, India, Mexico, and
the United States, and $GDPI_i$ for other countries in billions of U.S. dollars.
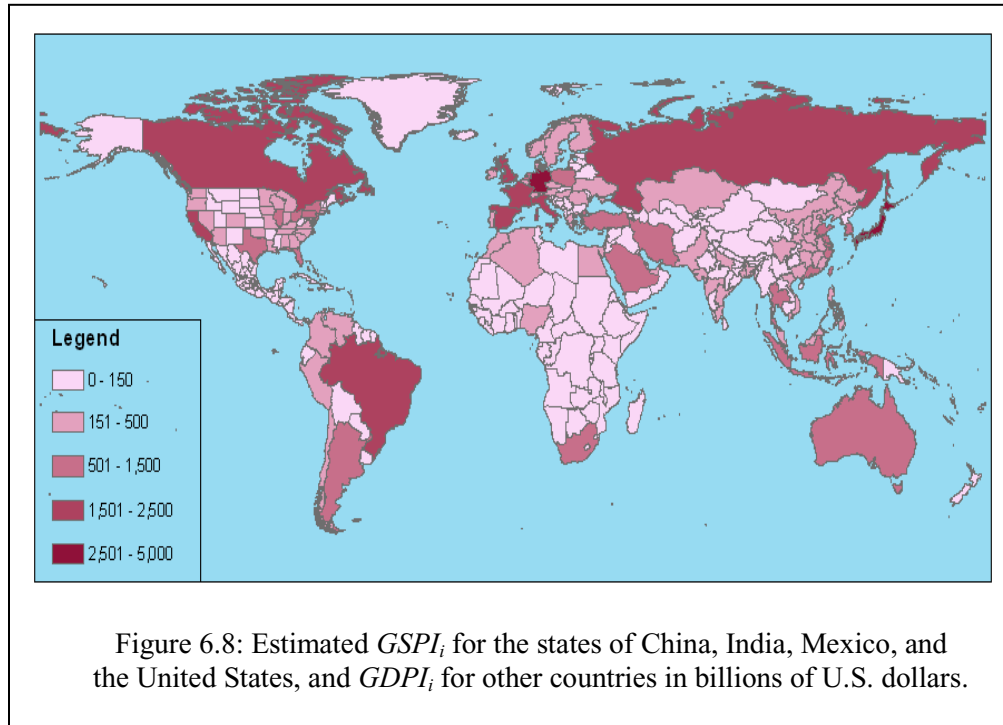
6.2.2 Creating a disaggregated map of total economic activity

The second part of the analysis involved spatially distributing the estimated total

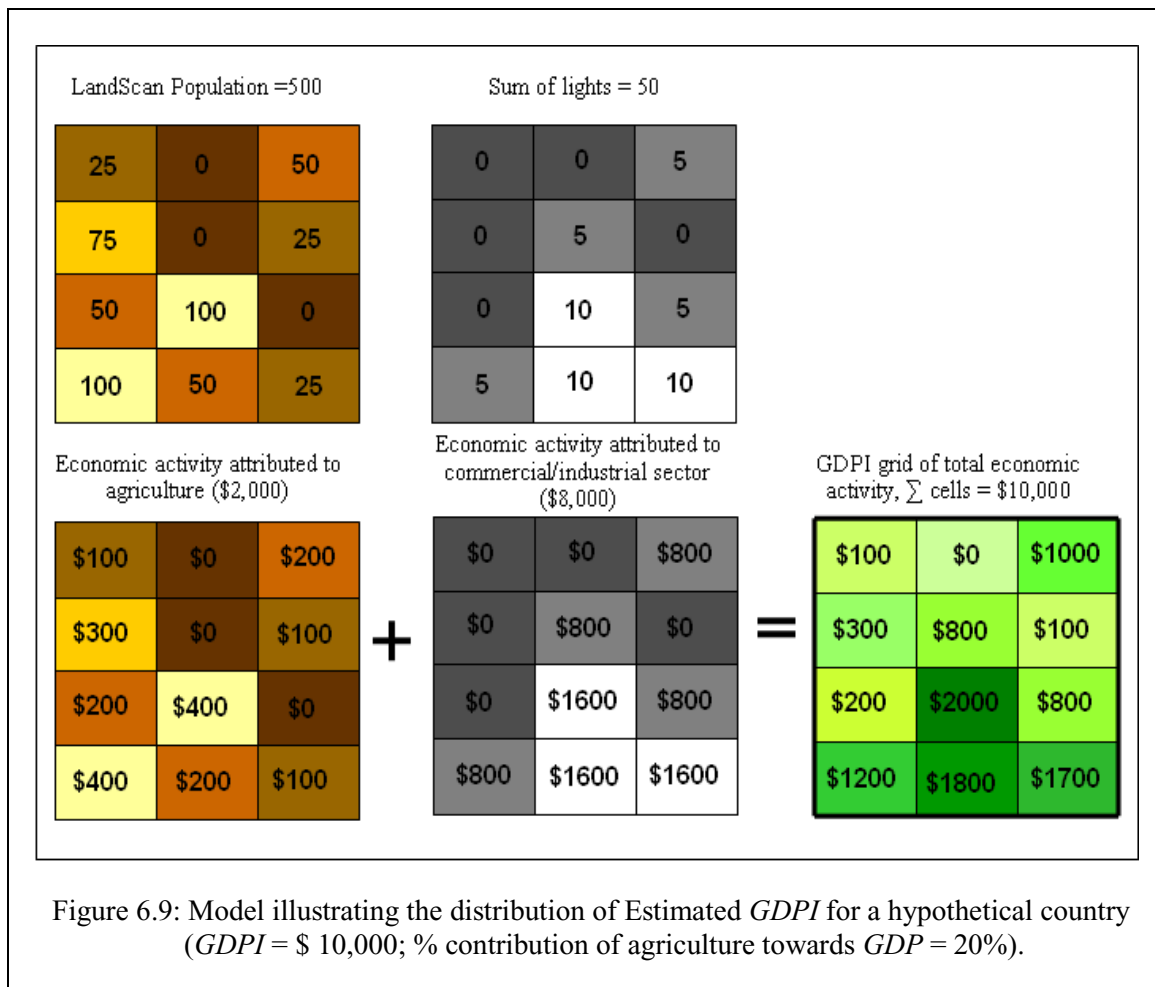economic activity to create a grid with a spatial resolution of 30 arc-seconds. A grid of

agricultural economic activity was created by distributing the percentage contribution of

agriculture towards economic activity for the administrative unit according to the

LandScan population grid. A grid of non-agricultural economic activity was created by

distributing the percentage of economic activity attributed to the commercial/industrial

sector according to the nighttime lights. The grids of agricultural and non-agricultural

economic activity were added to generate the grid of total economic activity.

To illustrate this process, a hypothetical country that has an estimated $GDPI$ of

$10,000, total population of 500, and a sum of lights value of 50, was used. The

percentage contribution of agriculture towards *GDP* for that country was assumed to be 20 percent. First, a grid of agricultural activity was created. This was done by distributing the economic activity attributed to agriculture (i.e., $2,000, in this example) according to the proportion of the population in each pixel of the LandScan population grid to the total population of the country (i.e., 500). Second, the grid of non-agricultural (or commercial or industrial) economic activity was created by distributing the remaining amount of *GDPI* (i.e., $8,000) according to the proportion of the brightness value of lights in each pixel of the nighttime lights grid to the sum of light value (i.e., 50) for the whole country. Finally, the disaggregated map of total economic activity was produced by adding the two grids of agricultural and non-agricultural economic activity for each administrative unit. The model is illustrated in figure 6.9.

Figure 6.9: Model illustrating the distribution of Estimated *GDPI* for a hypothetical country (*GDPI* = $ 10,000; % contribution of agriculture towards *GDP* = 20%).

6.3 Results –

The model shown in figure 6.9 was applied globally to generate the disaggregated map of total economic activity (figure 6.10). The disaggregated map represents values in millions of dollars assigned to one km^2 pixels, or millions of dollar per km^2 (i.e., $Mn/km^2). The pixels with a $0 value coincide with mountainous areas, deserts, and other inaccessible areas of continents. The pixels with the highest dollar values ($500 - $1278 Mn/km^2) lie in Singapore. Cities such as Shanghai, Hong Kong, Mexico City, and Washington, D.C., are in the next tier of wealthiest cities, having dollar values ranging

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between \$300 and \$500 Mn/km^2. Tokyo, Nagoya, Seoul, Kuwait, London, Madrid, Paris, New York, Los Angeles, are some of the cities which fall in the third tier of wealthiest cities, having dollar values ranging between \$200 and \$300 Mn/km^2. Most of the affluent areas of the world, such as capital cities and other major cities have dollar values ranging between \$20 and \$100 Mn/km^2.

Figure 6.10: Grid of total economic activity in millions of dollars per km^2 pixel.
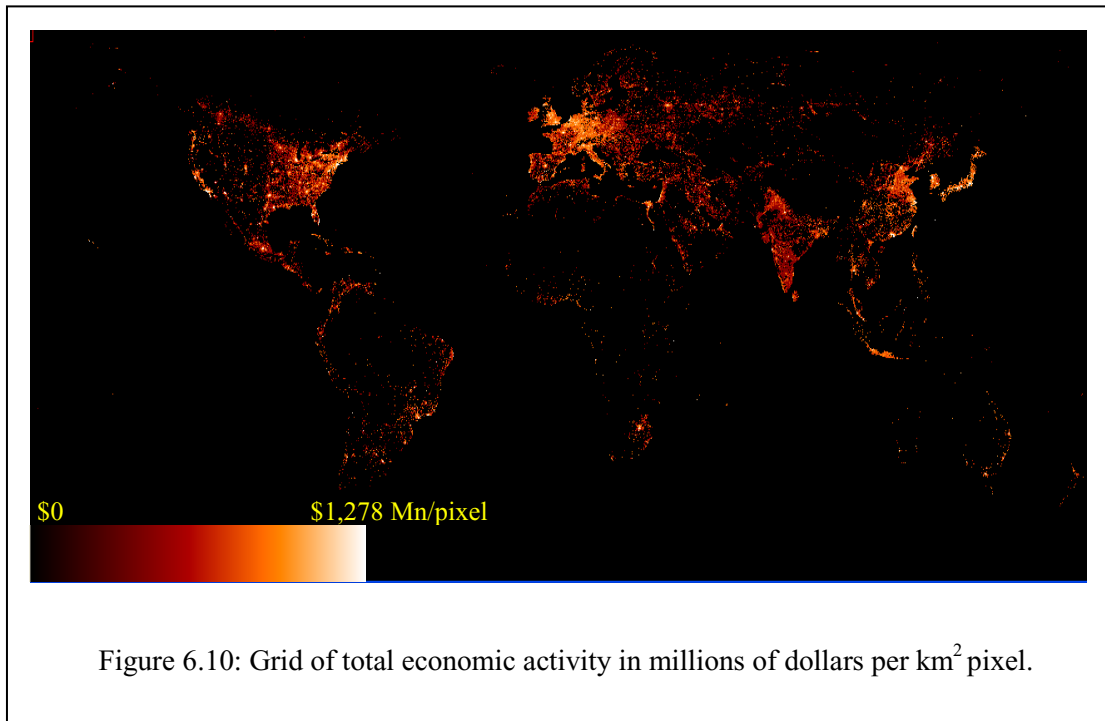
There is no way to validate the disaggregated map of economic activity other than comparing it with the aggregated official *GSP* values at the sub-national level for China, India, Mexico, and the U.S., and *GDP* values for the other countries, as official *GDP* and *GSP* values are easily available only at the national level and occasionally at the sub-national level. Thus, the disaggregated map of estimated total economic activity was aggregated to the country level and the state level (figure 6.8). Two difference maps were

created, one comparing the estimated total economic activity ($GSPI_i$ and $GDPI_i$) and official economic activity (GSP_i and GDP_i) (figure 6.11), and the second comparing estimated total economic activity to GSP or GDP with added informal economy estimates as estimated by Schneider ($GSPS_i$ and $GDPS_i$).
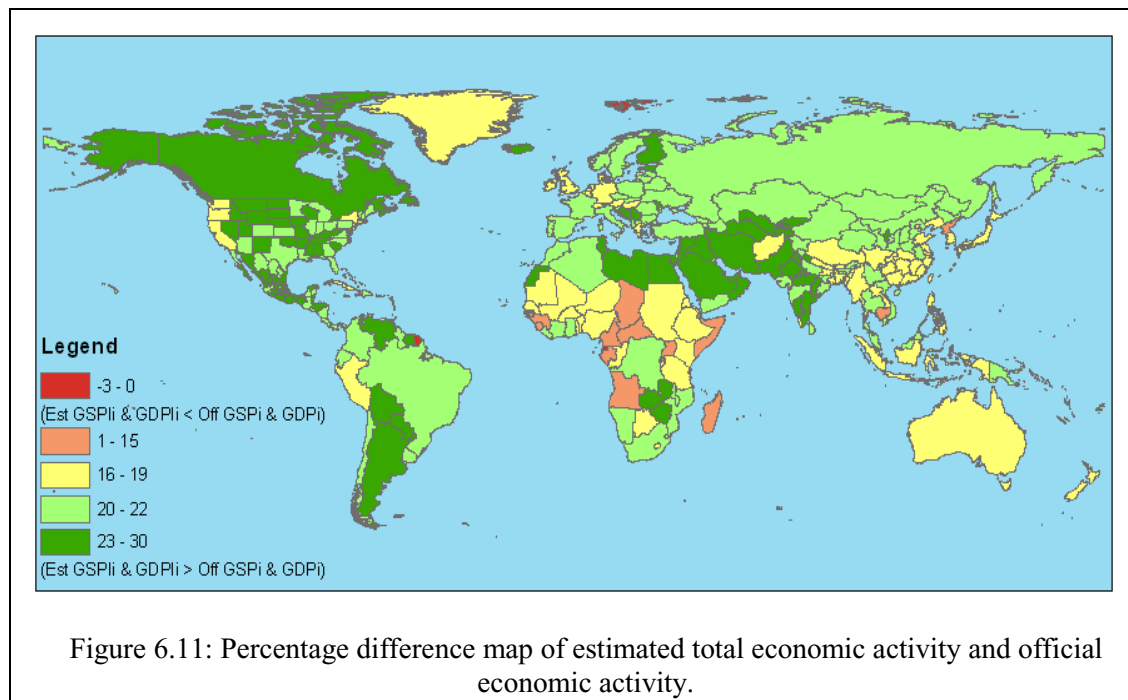
Figure 6.11: Percentage difference map of estimated total economic activity and official economic activity.

Figure 6.11 shows that estimated total economic activity was greater than official economic activity for almost all administrative units. This is expected, as unlike the official economic activity values, the estimated total economic activity values include the informal economy estimates. Estimated $GDPI_i$ values were thus up to 30 percent higher than the official GDP_i values, for both developed and developing countries. The only two countries for which the estimated $GDPI_i$ was less than the official GDP_i were the island countries of Maldives and Solomon Islands, possibly because the islands have very low

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population (Solomon Islands – 293,730, and Maldives – 405, as computed from the LandScan population grid of 2006) and have very few lit areas from which economic activity can be detected. At the sub-national level, estimated $GSPI_i$ was greater than official GSP_i by up to 30 percent for all the states of India and Mexico; for the U.S., estimated $GSPI_i$ was greater than official GSP_i by up to 30 percent for almost all the states; and for China, $GSPI_i$ was greater than GSP_i by up to 22 percent for all but one state (Ningxia).

Figure 6.12: Percentage difference map of estimated total economic activity and economic activity with added Schneider's informal economy estimates.
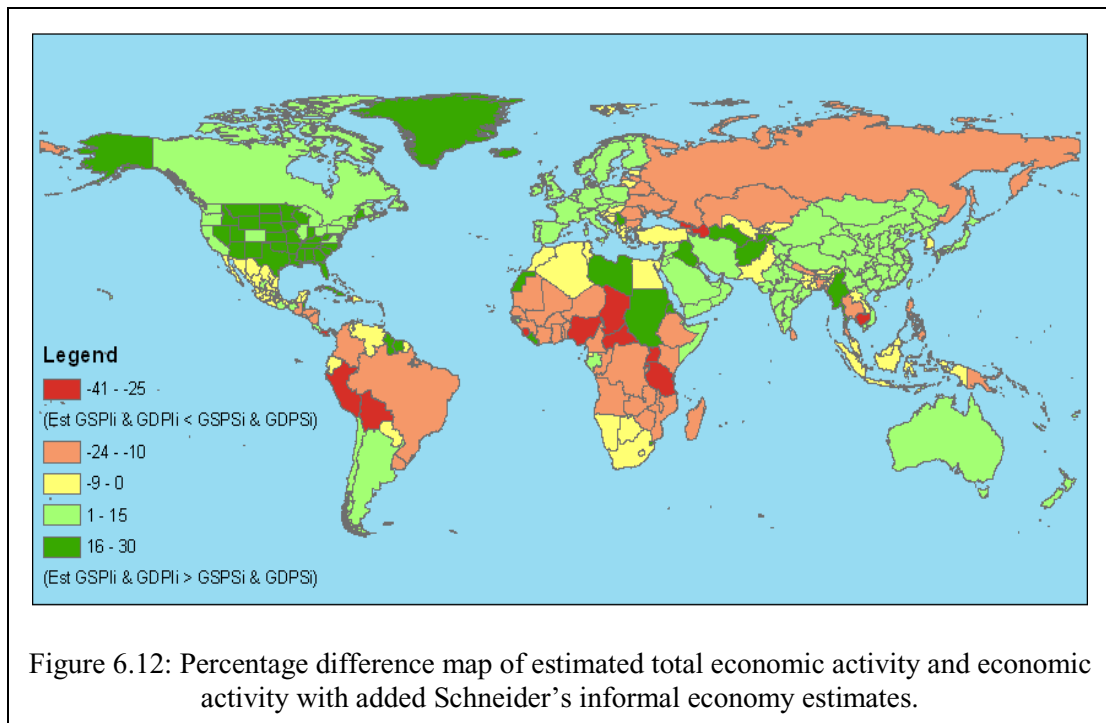
Since $GSPS_i$ and $GDPS_i$ (i.e., GSP and GDP with added Schneider's informal economy estimates) of the administrative units was used to calibrate the model for estimating $GSPI_i$ and $GDPI_i$ from the sum of lights, a percentage difference map between estimated $GSPI_i$, $GDPI_i$, and $GSPS_i$, $GDPS_i$ was made (figure 6.12). Estimated $GDPI_i$

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was greater than $GDPS_i$ for almost all the countries (with the exception of many of the African countries, Russia, and some of the South American countries) implying that Schneider may have underestimated informal economic activity for those countries. At the sub-national level, for most U.S. states, estimated $GSPI_i$ was greater than $GSPS_i$ up to 30 percent, and for China and India $GSPI_i$ was greater by up to 15 percent for most states. These results indicate that Schneider may have underestimated the informal economic activity in the U.S., China, and India. For most of the states of the Mexican Republic, however, estimated $GSPI_i$ was less than $GSPS_i$, indicating that Schneider may have overestimated the informal economic activity for the Mexican Republic.

6.4 Discussion -

A global grid of estimated total economic activity with a spatial resolution of one km^2 was generated based on the nighttime lights grid and the LandScan population grid. The greatest advantage of the disaggregated GDP map is that it offers immense analytical flexibility, because the data can be aggregated to units of different sizes. This could enable governments and analysts to track the economic growth of regions at different economic units of analysis and to implement appropriate measures and policies. This could also benefit researchers engaged in environmental, physical, or other socio-economic analysis, as they could aggregate the data to different ecological, physical, or social units.

Estimation of economic activity from the nighttime lights helps to overcome many of the problems associated with data collected through surveys, as the nighttime lights dataset are easily available and can be frequently updated. Economic censuses are usually

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conducted at intervals of 5-10 years, but the global coverage of nighttime lights data is available on a daily basis, and they are composited on a monthly and annual basis. Hence, nighttime lights data could serve as a proxy measure for estimating *GDP* for the inter-censal years.

The NGDC at NOAA is currently producing merged stable lights and radiance-calibrated products for the years 1996-97, 1999, 2000, 2003, and 2004. NGDC has also received approval from the Air Force for a new round of data collection at low, medium, and high gain settings, and these data will be used to produce a year 2010 radiance-calibrated nighttime lights product and subsequently a merged stable-lights and radiance-calibrated product for 2010. The coefficients estimated for 2006 could be used to estimate *GDP* for the merged nighttime lights product of 2010 and could also make it possible to estimate *GDP* for past years. Comparison of *GDP* estimates from the nighttime lights to official *GDP* statistics of past years and future years may provide useful insights as to the development of nighttime lights as a truly independent proxy measure of economic activity.

Many of the drawbacks which were noticed in some of the previous studies in trying to estimate economic activity from nighttime lights were addressed in this paper. The nighttime lights data which were used for this study were a merged stable lights and radiance-calibrated product, which shows brightness variations within city centers and helps to overcome the problem of saturation of city centers associated with stable lights images.

Doll et al. (2006) had noted the necessity of considering agricultural activity in the estimation of the total economic activity of a country. Since agriculture is a spatial

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activity, it is not only important to consider the percentage contribution of agriculture towards *GDP*, but also necessary to 'spread' the contribution of agriculture towards *GDP* in the 'fields'. The present analysis addressed this issue by distributing the percentage contribution of agriculture in the estimated $GDPI_i$ and $GSPI_i$ according to the LandScan population grid. Therefore, for countries such as India, China, as well as many of the African countries, where the agricultural contribution towards *GDP* is considerable, economic activity was distributed in the darker areas of each country, corresponding to rural population areas where there are people engaged in agricultural economic activity but there are no lights.

The approach presented in this paper is not a truly independent measure of economic activity because it still utilizes official *GDP* and *GSP* statistics and estimates of the informal economy in order to estimate regression coefficients. These regression coefficients vary dramatically as a function of the ratio of lights to economic activity for any given administrative unit. All previous disaggregated *GDP* maps which have been created to date using the nighttime lights data have relied on official statistics of *GDP* (Doll et al. 2000; Sutton and Costanza, 2002; Doll et al. 2005). For this paper, efforts were initially made to create the *GDP* grid using only the nighttime lights image and LandScan population grid. However, countries with large populations and relatively low lighting, such as China and India, defeated all attempts at developing a truly independent method (without relying on official statistics) for estimating economic activity. However, it can be anticipated that future longitudinal research of the relationships between nighttime imagery, population distribution, and the sectoral distribution of economic

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activity (i.e., agricultural, industrial, and service sectors) might contribute to the development of a more independent means of measuring economic activity from nighttime imagery.

The DMSP-OLS data have observational shortcomings, with coarse spatial and spectral resolution and lack of on-board calibration. These shortcomings will be addressed by the Visible Infrared Imaging Radiometer Suite (VIIRS) which will fly on the National Polar Orbiting Environmental Satellite System (NPOESS) during the next decade. The VIIRS will have on-board calibration and a higher spatial resolution (0.8 km) and spectral resolution. Nighttime lights data acquired at a higher spatial and spectral resolution will potentially facilitate creation of more accurate socio-economic maps.

Summary –

In this chapter a global disaggregated map of total economic activity, including both formal and informal economic activity was created from the nighttime lights and LandScan population grid, official estimates of *GDP* and *GSP*, and informal economy estimates. This provides an alternative means of measuring global economic activity which could be updated on an annual and semi-annual basis. The inclusion of informal economic activity is a primary advantage of this disaggregated economic map as informal economic activity is often excluded from the official estimates of economic activity. Also, the disaggregated map could be aggregated to different units of analysis and be integrated with other physical and environmental data which are available in raster format.

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CHAPTER 7

CONCLUSION

This research explored the use of nighttime light images in conjunction with other datasets such as the LandScan population grid, official statistics of economic activity of countries at the national and sub-national level, and informal economy estimates, to estimate economic activity of countries at the sub-national and national level, and to create a disaggregated global map of estimated total economic activity. The central motivating force underlying this research has been to develop alternative methods of estimating economic activity in order to address the inaccuracies and gaps in the official statistics of economic activity. This is especially true of the developing countries where the informal economy contributes a significant proportion to the official statistics but is often excluded. The methodologies developed using the nighttime lights images along with other datasets may have their own shortcomings, but nevertheless they provide alternative and innovative solutions. While none of the datasets are free of error, it can be assumed that a combination of several datasets having the 'right' kind of measurement errors might help to minimize the errors of the final product. This assumption is based on Browning and Crossley's (2009) study in which they suggested that it is perhaps easier to design socio-economic survey questions with two or more 'right' kind of measurement errors, which provide better information about the distribution of the quantity of interest

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than attempting to design survey questions without measurement errors. Thus, they rightly concluded: 'It is better to have several error-prone measures than one.' This has been the underlying philosophy of this research.

In chapters four and five, models were developed on the basis of the spatial relationship of the nighttime lights data and the adjusted official Gross State Product of the U.S. to estimate the informal economic activity and remittances for Mexico and India, which are often unaccounted for in the official statistics. In this case, two different datasets were used to develop an independent method of estimating the informal economic activity and remittances for two developing countries from the nighttime lights imagery. In chapter six, five different datasets – the nighttime lights data, the LandScan population grid, official estimates of economic activity at the national and sub-national level, informal economy estimates, and percentage contribution of agriculture towards *GDP* were used to create the disaggregated map of total economic activity. Thus it can be presumed that using the nighttime imagery in conjunction with all these datasets, which have their own sets of errors, would provide a much better estimate of economic activity than using either of these datasets alone.

The analyses were based on the striking correlation between the spatially explicit nighttime light images and distribution of wealth and urban population of countries. It was also based on the allometric relationship between lit areal extent and population which has been described and utilized by Nordbeck (1965) and Tobler (1969) among others and can be expressed as a 'law' in geography. The lit areas of the nighttime light image being associated exclusively with human activities makes it uniquely poised for estimation of economic activity via the allometric relationship between lit area and urban

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population. Assuming that population could act as a substitute for economic activity for countries at the sub-national level when accurate statistics of economic activity at the sub-national level are not available, estimated urban population of the U.S. states was derived based on a slight modification of the allometric relationship between lit areal extent and corresponding urban population of the U.S. states. The estimated urban population and ostensibly more reliable official statistics of *GSP* for the U.S. were then used to estimate sub-national economic activity for the U.S. The strong association (correlation coefficient, R = 0.84) between the official *GSP* and estimated *GSI* for the U.S. showed the feasibility of this approach for estimating the economic activity for Mexico and India on the basis of the parameters derived through the regression relationships developed for the U.S.

Also, since it was assumed that economic activity associated with urban populations creates the same spatial patterns of nighttime lights in the U.S., Mexico, and India, the U.S. parameters could be used to estimate economic activity in Mexico and India, and the excess of economic activity measured from the nighttime lights relative to the official statistics could be attributed to the informal economic activity and remittances. Therefore, the nighttime lights provided an independent estimate of economic activity including informal economy and remittances for Mexico and India which are often excluded from the official statistics.

However, these analyses also highlighted some drawbacks in using the nighttime lights imagery as a proxy measure of economic activity. For states with very dense population such as New York and California in the U.S., Mexico City in the Mexican Republic, and Maharashtra and West Bengal in India, economic activity estimated from

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estimated urban population which in turn was estimated from lit urban areas of nighttime lights imagery, was underestimated. Although it is generally assumed that the light usage per person would increase as income rises the relationship becomes complicated in case of these highly urbanized and densely populated states because with the construction of high-rise building people live above one another and some light is blocked in reaching space. Again, within prosperous regions or states, the use of lighting technology is also changing by the use of outdoor light shades and shields to prevent light pollution of the night-sky and conserve energy. This also acts as a confounding factor when wealth is estimated from the nighttime light images (Elvidge et al. 2009a).

Also, in the case of India, the estimated *GSP* of the states and UTs from the spatial patterns of the nighttime lights demonstrated a strong association with the official *GSP* statistics with a correlation coefficient (r) of 0.93, but it underestimated *GSP* of most of the states and UTs. Thus, although the assumption that economic activity associated with urban populations creates the same spatial patterns of nighttime lights for countries may be valid, if the countries have different levels of urbanization, the method may not be appropriate. India and the U.S. had different levels of urbanization in comparison to almost the same levels of urbanization of Mexico and the U.S. Thus the estimated Gross Domestic Income of India had to be adjusted by multiplying it with the ratio of the percent urban population in the U.S. to percent urban population in India and then the underestimated informal economic activity and remittances in the official statistics was estimated. Therefore, it can be concluded that this method would be useful in estimating the informal economic activity and remittances in the official statistics for countries which have the same levels of urbanization.

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Acknowledging the fact that this approach of estimating informal economic activity and remittances from the nighttime lights is still in its elementary stages, a few avenues for future research can be suggested. First, if reliable official statistics of *GDP* and *GSP* for countries at different levels of development can be obtained then there would be a possibility of building separate models for Upper -, Middle-, and Low-Income countries instead of depending on the official statistics of only a single developed country. Second, it would also perhaps be possible to obtain better estimates of informal economy and remittances if countries are grouped on the basis of their levels of urbanization, and the parameters derived from the spatial relationship of nighttime lights and the most reliable official *GSP* and *GDP* values of a single country from each group are used. Third, another potential area of future research would be to compare the informal economy estimates obtained from the existing indirect approaches (the Currency Demand Approach, the Physical Input Method or Electricity Consumption Method, and the DYMIMIC method) and the nighttime satellite image. Then a method could be developed by using the nighttime imagery in complement with the existing indirect methods, or using the sum of light intensity values as a variable in the indirect approaches of estimating informal economic activity.

In the sixth chapter, the disaggregated map of total economic activity which was created was based on the close spatial relationship between the sum of light intensity values and official *GDP* or *GSP* values which was observed in some of the previous studies. However, the empirical relationship between the sum of lights and official statistics of the administrative units showed that the administrative units may be brighter or dimmer relative to their levels of economic development. Therefore, the administrative

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units had to be grouped on the basis of the ratios of their sum of lights and official *GDP* or *GSP* and through subsequent analysis unique coefficients were determined with which the sum of lights were multiplied to derive the estimated *GDPI* or *GSPI* for each of the administrative units. Moreover, this disaggregated map of total economic activity which was created from the nighttime lights image and the LandScan population grid is not an independent estimate of economic activity as the sum of lights were calibrated to the official *GDP* or *GSP* with added informal economy estimates for the administrative units. Also, the discordant relationship between population and sum of lights for countries such as China and India, which have a much larger population relative to their spatial distribution of lights, defeated the attempts at developing an independent method for estimating economic activity. Nevertheless, a disaggregated map of total economic activity was created at one km^2 resolution which distributed the percentage contribution of agriculture towards economic activity of countries on the basis of the LandScan population grid and the contribution of the commercial/industrial sector on the basis of the nighttime lights imagery. The *GDP* grid created in the sixth chapter in fact forged to address all the drawbacks which were noticed in previous attempts at creating a disaggregated map of economic activity.

Some future research possibilities for creating better maps of economic activity and perhaps develop independent methods for estimating economic activity can be suggested. One possible method worth exploring would be to categorize the countries on the basis of the contribution of the different sectors (i.e., the agricultural, industrial/commercial and service sector) towards economic activity and subsequently explore the prospect of developing independent estimates of economic activity by using sum of lights from the

nighttime satellite imagery and incorporating population numbers derived from the LandScan population grid. Furthermore, using the coefficients derived from the analysis using the nighttime lights of 2006 to estimate the *GDP* and *GSP* of the administrative units for other years and comparing them to the published official statistics might also provide some ideas for developing independent estimates of economic activity. It can also be anticipated that the availability of imagery at a higher spatial (0.8 km) and spectral resolution from the VIIRS which will fly on the NPOESS during the next decade might facilitate the creation of improved socio-economic maps.

However, there are some caveats which should be kept in mind when using the coefficients derived from the nighttime image of one year to estimate economic activity of other years. For instance, the satellite overpass time for F162006 was between 8:09 and 8:13 pm (this is probably the best time for observation of maximum extent of lighting in all regions) and that of the most recent launch of F182010 is before 8 pm. This earlier overpass time of F182010 may result in reductions in data coverage due to solar contamination in the mid-and high- latitudes in the summer months. So, when the coefficients derived from F162006 are used to make estimates of economic activity for the data collected by the satellite-year F182010 it may lead to underestimation of economic activity for the year 2010. The absence of a consistent overpass time of the different satellites of the different years is a factor to be taken into consideration in any future estimation of economic activity.

It would also be interesting to explore what effect the global economic recession would actually have on the spatial distribution of the nighttime lights. The global economic recession has stalled the progress towards the achievement of the Millennium

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Development Goals and has in fact pushed 55 to 90 million more people into extreme poverty in 2009. The International Labor Organization (ILO) estimates that the global unemployment in 2009 could reach between 6.3 and 7.1 percent by the end of 2009 (United Nations 2009). The worsening employment situation has in effect forced more people to join the vulnerable informal economy. Since in this research any excess of economic activity (over what is accounted for in the official statistics) measured from the spatial patterns of nighttime lights has been attributed to informal economy and inflow of remittances, does it mean that with an increase of informal economic activity due to global economic recession there would be greater spread of nighttime lights? Or would economic recession, pushing more people into poverty, cause more lights to dim out? These are indeed puzzling questions and require much more thorough investigation.

Nonetheless, this research demonstrates the enormous potentiality of the nighttime lights for estimating economic activity of countries at the national and sub-national level. Taking into consideration the continuous growth of population, the ever-changing economy in the era of globalization, the volatility associated with informal economic activity and unrecorded remittances, there will always be an issue with regards to the credibility of the official estimates of informal economic activity and remittances. These economic maps created from nighttime lights may provide economists and policy makers alternative means to better understand the economic situation of countries, detect the shortcomings in economic structures, improve employment opportunities, reduce poverty, undertake other constructive development policies, and monitor the economic recovery of countries.

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APPENDIX

List of Publications

Journal Articles:

Peer-reviewed

Ghosh, T., R.L. Powell, S. Anderson, P.C. Sutton, and C.D. Elvidge. 2010. Informal economy and remittance estimates of India using nighttime imagery. *International Journal of Ecological Economics and Statistics* 17(P10): 16-50

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