Estimating the Information and Technology Development Index (IDI) Using Nighttime Satellite Imagery

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Abstract: The International Telecommunication Union (ITU) has developed a tool known as the Information and Communication Technology Development Index (IDI) for measuring the development of countries as information societies. They found a close correlation between IDI and the Gross Domestic Product (GDP) per capita of countries. In this paper on the basis of this relationship we have tried to create a 30 arc-second grid of IDI. At first a disaggregated map of total economic activity was created from the Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS) merged radianc-calibrated nighttime image of 2006 and the LandScan population grid of 2006. The GDP per capita was then calculated and an attempt was made to create the IDI grid. However, at the 30 arc-second resolution the GDP per capita was found to be less in the city centers than in the areas surrounding the city centers. Thus an estimated IDI grid at 30 arc-second resolution could not be created based on the relationship between GDP per capita and official IDI. Therefore, the finest resolution at which the estimated IDI map was
created was at the state level for the South-East Asian countries. In a future endeavor, we intend to create an IDI grid of much finer resolution.

**Keywords:** Information and Communication Technology Development Index (IDI), DMSP-OLS Nighttime satellite imagery, LandScan population grid

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1. Introduction

In spite of the global economic recession both developed and developing countries have been making considerable progress in becoming information societies. The International Telecommunication Union (ITU), a United Nations agency, has developed a tool known as the Information and Communication Technology Development Index (IDI) to measure the development of countries as information societies. The IDI is a composite index made up of 11 indicators covering Information and Communication Technology (ICT) use, access, and skills. The access sub-index encapsulates ICT readiness and includes five infrastructure and access indicators (fixed telephony, mobile telephony, international internet bandwidth, households with computers, and households with internet). Use sub-index depicts ICT intensity and includes three ICT intensity and usage indicators (internet users, fixed broadband, and mobile broadband). The skills sub-index capturing ICT capability or skills as indispensable input indicators is based on three proxy indicators (adult literacy, gross secondary and tertiary enrolment). Because it is based on proxy indicators the skills sub-index has less weight in the computation of the IDI compared to the other two sub-indices [1].

The close correlation between IDI and income per capita has been well established by ITU. Many of the indicators included in the IDI have also been seen to be strongly correlated with Gross Domestic Product (GDP) per capita [1]. This close relationship provided the idea for this research paper. In a previous research, a 30 arc-second grid of total economic activity was created from the Defense Meteorological Satellite Program’s Operational Linescan System (DMSP-OLS) nighttime satellite imagery and the LandScan population grid [2]. Because of the close correlation between IDI and GDP per capita, research questions were put forward regarding the possibility of identifying the countries or states within countries, which were moving ahead or lagging behind in IDI based on variations in the GDP per capita versus the reported IDI. Also, there is the possibility of creating a grid or a fine resolution image of IDI using DMSP nighttime lights data, indicating the variation in IDI levels within a country.

The first part of the analysis involved creating the GDP grid and the second part of the analysis involved examining the possibility of creating an IDI grid, with special focus on the South-East Asian countries.
2. Data Used

2.1. Nighttime Lights Imagery

The nighttime lights image was used to calculate the sum of light intensity values for each country and the states of United States (U.S.), Mexico, China, and India (hereon, will be addressed as administrative units) 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 cloud-free stable lights and radiance-calibrated nighttime image of 2006, processed and archived at the National Geophysical Data Center (NGDC) of the National Oceanic and Atmospheric Administration (NOAA) was used to estimate total economic activity of each administrative unit [3,4]. 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 [4]. The National Geophysical Data Center (NGDC) of the National Oceanic and Atmospheric Administration (NOAA) has been archiving and processing Defense Meteorological Satellite Program’s Operational Linescan System (DMSP-OLS) nighttime lights data since 1994. The composited nighttime images are resampled and georeferenced to 30 arc-second grids, equivalent to approximately 1 km² at the equator. The latitudinal extent of the dataset is from 75°N to 65°S and the longitudinal extent is from 180°W to 180°E (Figure 1).
2.2. 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 population grid was also used to estimate the aggregate population of the countries, which were used to compute GDP per capita in the second part of the analysis. The U.S. Department of Energy at Oak Ridge National Laboratory has produced a progressive series of spatially disaggregated global population count datasets. The cells have integer population counts representing ambient population distribution. The dataset has a spatial resolution of 30 arc-seconds [5]. For this 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 2).

![Figure 2. LandScan population grid of 2006.](image)

2.3. 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 [6]. 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 for those countries, data were taken from the Central Intelligence
Agency (CIA) World Factbook [7]. All official GDP data were expressed in Purchasing Power
Parity (PPP) U.S. dollars.

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 [8]; for Mexico, from Instituto
Nacional de Estadistica Geografia [9]; for the provinces, municipalities, autonomous regions,
and Special Administrative Regions of China, from the National Bureau of Statistics of China
[10]; and for India, from the Central Statistical Organization [11]. 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.

2.4. Informal Economy Data

Informal economy is present in both the developed and developing countries [12]. 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. In this study the estimates made by Schneider using the dynamic multiple-indicators
multiple-causes model (DYMIMIC) was used [13,14]. Schneider [13] used the DYMIMIC
model to estimate the informal economy (which he calls the shadow economy) as a percentage of
“official” GDP and provided 2005 percentage estimates of the informal economy for 96
developing countries, and 2006 percentage estimates for 21 Organization for Economic
Cooperation and Development (OECD) and 25 transition countries. In the present study, the
percentage informal economy estimates were added to the GDP of each country (GDPSi) 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 (GSPSi).

2.5. Percentage Contribution of the Agricultural Sector

Agriculture is an important economic activity, especially in developing countries. However,
since agriculture corresponds to the darker areas of the world, it cannot be depicted by the
nighttime lights imagery. Therefore, the percentage of estimated total economic activity
attributed to agriculture was spatially distributed according to the LandScan population grid.
Data on the percentage contribution of agriculture towards GDP at the national level was
acquired from the World Development Report of 2008 [15] and from the CIA World Factbook [7]. 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.

2.6. Information and Technology Development Index (IDI) of countries

The IDI of 159 countries for the year 2007 were available from the data collected and computed by the ITU. Countries with higher GDP per capita have higher IDI than countries with lower GDP per capita [1]. Figure 3 shows the official IDI of the countries of the world.

![IDI map of the countries of the world, 2007.](image)

**Figure 3.** Official IDI map of the countries of the world, 2007.

3. Method and Results

The first part of the analysis involved creating the disaggregated map of total economic activity [2] and the second part of the analysis involved making an attempt to create an IDI grid. In order to create the GDP grid the first step involved computing the sum of light intensity values within each of the administrative units (SLi) from the merged nighttime lights image of 2006. Regressing the sum of lights (SLi) against official GDPi or GSPi showed that countries may be
brighter or dimmer in comparison to what was expected based on reported GSP\textsubscript{i} or GDP\textsubscript{i} values. This examination indicated that grouping the administrative units based on similar ratios between sum of lights (SL\textsubscript{i}) and GSP\textsubscript{i} or GDP\textsubscript{i} would provide better relationships between the sum of lights (SL\textsubscript{i}) and GSP\textsubscript{i} or GDP\textsubscript{i}. Ratios (R\textsubscript{i}) of the sum of lights (SL\textsubscript{i}) to the official GSP\textsubscript{i} or GDP\textsubscript{i} for each administrative unit were calculated as follows:

\begin{equation}
R_i = \frac{SL_i}{GSP_i}
\end{equation}

or,

\begin{equation}
R_i = \frac{SL_i}{GDP_i}
\end{equation}

Figure 4 represents the map of the ratios of the sum of lights (SL\textsubscript{i}) to the official GSP\textsubscript{i} or GDP\textsubscript{i} for each administrative unit. The lower the ratio, the dimmer the administrative unit is relative to the level of economic development as measured from its official GSP\textsubscript{i} or GDP\textsubscript{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\textsubscript{i} or GDP\textsubscript{i} statistics.

![Figure 4](image)

**Figure 4.** Map of the ratio of sum of lights (SL\textsubscript{i}) to GSP\textsubscript{i} or GDP\textsubscript{i} for each administrative unit.

Grouping the administrative units based on the ratios (R\textsubscript{i}) gave rise to 36 groups. For each of the groups, the sum of lights (SL\textsubscript{i}) were calibrated to the official GSP\textsubscript{i} or GDP\textsubscript{i} with added informal economy estimates (i.e., GSP\textsubscript{S} or GDP\textsubscript{S}) \cite{13, 16, 17} through regression models. The intercept was set to zero and coefficients of determination (R\textsuperscript{2}) greater than 0.9 was obtained for all the 36 groups. The regression models provided beta coefficients (β\textsubscript{j}) for each group (where \( j \))
refers to the group index). Figure 5 shows a subset of the regression models for the groups of administrative units, where group 1 has the lowest \( R_i \) values, and the 36th group has the highest \( R_i \) values.

![Graph](image1)

First group

![Graph](image2)

Thirty-sixth group

**Figure 5.** Regression models for estimating coefficients for sample groups

Through tests conducted between the different variables, an empirical relationship was observed between the ratios \( R_i \) of each administrative unit and the estimated coefficients \( \beta_i \) across all groups. This relationship was described by a natural logarithmic function between the two variables (Equation 3). Exponentiating \( \ln (\beta_i) \) provided unique coefficients for each of the administrative units \( (\beta_i') \) (Equation 4). The logarithmic regression graph is shown in Figure 6.

\[
\ln (\beta_i) = 0.58 - 0.95 \cdot \ln (R_i) \quad (3)
\]

\[
\beta_i' = \exp (0.58 - 0.95 \cdot \ln (R_i)) \quad (4)
\]
Figure 6. The logarithmic regression to derive estimated unique coefficients, where $R_i =$ ratio of sum of lights to GSP or GDP and $\beta_j =$ Estimated group coefficient

After deriving 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 5 and 6).

$$\beta_i' \times SL_i = GSPI_i$$  \hspace{1cm} (5)

$$\beta_i' \times SL_i = GDPI_i$$  \hspace{1cm} (6)
The estimated total economic activity was spatially distributed to create a disaggregated 30 arc-second map of total economic activity. 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. The disaggregated map represents values in millions of dollars assigned to 1 km² pixels, or millions of dollar per km² (i.e., $Mn/km²).

![Grid of total economic activity in millions of dollars per km² pixel.](image)

**Figure 7.** Grid of total economic activity in millions of dollars per km² pixel.

In the second part of the analysis, in order to create the IDI grid, at first, the disaggregated map of total economic activity was aggregated to the country level for all countries of the world. Then, the aggregated GDP of the countries were divided by the population of the countries to get the estimated GDP per capita values. Figures 8 (a) and (b) show the estimated GDP per capita of all countries and the South-East Asian countries, respectively.
Figure 8. (a) Estimated GDP per capita of the countries of the world, (b) Estimated GDP per capita for the South-East Asian countries.
Next, a second degree polynomial regression relationship was observed between the estimated GDP per capita values and the official IDI values, and this regression relationship, with an $R^2$ of 0.89 provided estimated IDI values for the countries of the world (Equation 7, Figure 9). The ‘outlier countries’ Brunei, Kuwait, United Arab Emirates (UAE), Qatar, Luxembourg, and Norway were taken out from the regression analysis; and estimated IDI values were obtained for all countries which had official IDI values. The data can be downloaded at http://www.ngdc.noaa.gov/dmsp/download_idi.html.

$$y = 1.58 + (148.06 \times x) - (1944.46 \times (x - 0.0142)^2)$$  \hspace{1cm} (7)
Figure 10. Official IDI versus estimated IDI for the countries of the world

Figure 10 demonstrates the official versus estimated IDI values along with a 1:1 line. The official IDI plotted against estimated IDI shows a strong association with a Pearson’s correlation coefficient (R) of 0.97.

In the next step, using Equation 7 we tried to create an estimated global 30 arc-second IDI grid but it was giving erroneous results at that resolution. The reasons for these erroneous results will be discussed in a later section. Since creating a 30 arc-second resolution grid did not work, the next finest resolution at which the estimated IDI map was created was at the state level for the South-East Asian countries (Figure 11). A difference map of the estimated and official IDI of the South-East Asian countries was also created at the country level (Figure 12).
The estimated IDI map at the state level (Figure 11) shows that the largest areas with low levels of IDI lie in the states of Myanmar and Papua New Guinea. Highest levels of IDI were estimated for the states of Brunei and around the Bangkok metropolis in Thailand. To identify the countries that are moving ahead, falling behind, or are about where expected in their IDI development, we differenced the GDP per capita-estimated IDI from the reported IDI. Our hypothesis is that countries, for which the reported IDIs are higher than the GDP per capita-estimated IDIs, are moving ahead with their IT infrastructure development. Conversely, countries where the GDP per capita-estimated IDIs are higher than the reported IDIs are lagging behind in their IT infrastructure development. The results of this analysis are shown in Figure 12. We found that Vietnam and the Philippines are “moving ahead” with reported IDI’s that exceed the GDP per capita estimated IDI values. Countries that have reported IDI’s that are slightly ahead of what would be expected based on their GDP per capita include Myanmar,
Thailand and Indonesia. Countries where the reported IDI is a close match to the GDP estimated IDI include Laos and Cambodia. Malaysia was found to be slightly behind in their reported IDI development relative to GDP per capita. Papua New Guinea is lagging behind, with a reported IDI that is clearly lower than that estimated from GDP per capita.

![Estimated IDI minus Official IDI](image)

**Figure 12.** Difference between estimated and official IDI for the South-East Asian countries. Red and orange indicates that the country is “moving ahead” with IT development. Yellow indicates that the IDI is about where expected. Green indicates that the reported IDI is lower than anticipated based on the GDP per capita. Note East Timor has not reported IDI value.

4. Discussion
After creating a global grid of estimated total economic activity an attempt was made to create a grid of estimated IDI based on the regression relationship between official IDI and estimated GDP per capita of the countries. However, at the 30 arc-second resolution the city centers were seen to have lower GDP per capita in comparison to areas just outside the city centers, and so the regression relation between official IDI and estimated GDP per capita could not be employed to create the IDI grid. This is illustrated in Figure 13 by drawing a transect across Hanoi, Vietnam. The spatial profile depicts this phenomenon. The very high population numbers in the city centers may have been causing this occurrence, because although the GDP values are the highest in the city centers, dividing the GDP values with the high population numbers lowers the ratio.

**Figure 13.** Transect across Hanoi, Vietnam depicting the low GDP per capita in the city centers

Since creating the IDI grid at the 30 arc-second resolution was not possible, the estimated IDI map was created at the state level and country level for the South-East Asian countries. At the country level, Figure 12 shows that estimated IDI was less than official IDI for Vietnam and Philippines, implying that factors other than GDP per capita might have contributed to their higher official IDI values. Factors such as vigorous government initiatives to build IT infrastructure, low prices at which the information and communication technologies (ICT) are available, increasing literacy levels of the population, and cultural adaption to use of mobile IT
devices may be some of the other factors which have encouraged the use of ICT in these countries and raised their IDI levels. Thus, these countries are moving ahead as information societies and factors besides GDP per capita are contributing to their development. On the other hand, GDP per capita estimated IDI was greater than official IDI for Papua New Guinea and Malaysia, which meant that estimated GDP per capita was of paramount importance in determining their IDI values and other factors such as government initiative, prices of ICT, literacy levels of the population, were not that important in encouraging the use and access of ICT in these countries. Thus, these countries for which the official IDI was less than estimated IDI have been lagging behind in government initiatives, or in the social and economic infrastructure required to promote the rapid spread of ICT access and use.

Although a 30 arc-second grid of IDI could not be created the ‘reasonable’ results shown in the spatial map of estimated IDI at the state level and the country level for the South-East Asian countries authenticates the significance of this method in estimating IDI from the nighttime lights imagery at different levels of spatial aggregation. In a future endeavor we wish to experiment with creating estimated IDI maps at levels of spatial aggregation higher than 1km² by aggregating the nighttime lights image and the LandScan population grid to higher spatial resolutions.

5. Conclusions

This research focuses on creating a fine resolution image of Information and Technology Development Index (IDI), with special emphasis on the South-East Asian countries. The GDP grid created from the nighttime lights image and the LandScan population grid was used for achieving this purpose. An effort to create the IDI grid was based on the second degree polynomial regression relationship between the official IDI values and the estimated GDP per capita of countries. However, creation of the grid at 30 arc-second resolution was not successful because of the low GDP per capita ratio in the city centers. Nevertheless, in order to test the rationale of the method an estimated IDI map of the South-East Asian countries was made at the state level and country level, which provided encouraging results. Because of these encouraging results it can be safely assumed that the nighttime lights image in combination with the LandScan population grid are capable of producing IDI maps at finer resolutions than simply at the national level.

The global nighttime light mosaics are made on a monthly, quarterly, and annual basis. Besides, the NGDC at NOAA is currently producing superior merged stable lights and radiance-calibrated nighttime lights products for the years 1996-97, 1999, 2000, 2003, 2004, and 2010. The method developed in this paper could be used to create fine resolution maps of estimated IDI for other years using the merged nighttime lights imagery and the LandScan population grid.
The information and communications technologies (ICT) have promoted tremendous socio-economic development, including productivity gains, and development of new technologies, facilitating trade in the service sectors, providing more employment in ICT-related sectors, providing enhanced flexibility for firms and workers, improving education performance, and enabling more women to participate in the employment workforce [1]. With the availability of ICT maps at finer resolutions the government and policy makers will be able to focus on smaller areas which maybe lagging behind in ICT development and take appropriate measures to promote ICT development in those areas. Thus, the nighttime lights images and the LandScan population grid provides a quick, efficient, and innovative method of creating IDI maps at finer resolutions. Our future endeavor will be directed towards refining the method and striving to create the IDI grid at resolutions finer than at the state level.

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