GLOBAL MAPPING OF HUMAN SETTLEMENT
Experiences, Datasets, and Prospects

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Global Urban Mapping Based on Nighttime Lights

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6.1 INTRODUCTION

Urban places may be broadly defined as settlements where most people live and work. Human beings worldwide tend to cluster in spatially limited habitats occupying less than 5% of the world’s land area. The density of infrastructure — or “urban-ness” — can be viewed as a continuum ranging from wilderness at one extreme to central business districts at the other extreme (Weeks, 2004). Because of their key role in sustaining human civilization and their impact on the environment, there is substantial interest in global mapping of human settlements and updating such maps on a routine basis.

Satellite sensors provide one of the few globally consistent and repeatable sources of observations. In the environmental sciences, satellite data have proven crucial for global mapping and global assessment of processes such as deforestation. Fewer applications for satellite data have been developed in the social and economic sciences. In part, this can be attributed to the fact that most Earth observation satellite sensors are optimized for observation of natural phenomena (e.g., the movement of clouds and the characteristics of the land and sea surface) that are not directly related to socioeconomic measures such as population density, living conditions, and economic activity. The physical structures of urban areas produce distinctive spatial and spectral signatures that are recorded by many types of remotely sensed data.
However, no satellite sensor has been designed and flown specifically for mapping and monitoring urban areas.

With moderate (10–50 m) resolution imagery, it is possible to map the extent of urbanized land and delineate basic urban classes such as commercial/industrial, residential, and open areas such as parks with reasonable accuracy. With high spatial resolution imagery (~1 m), it is possible to outline individual buildings and with stereo imagery estimate the volumes of individual structures.

To date, an openly accessible global urban map has not been produced from moderate- or high-resolution satellite imagery. Although it is possible to collect a sufficient quantity of cloud-free moderate resolution imagery for such a map in a single year, the generation of an urban map from sources such as Landsat is complicated by the lack of a uniform spectral or spatial signature for urban areas (Small, 2005). Collection and processing difficulties combine to frustrate the production of a global urban map from high spatial resolution satellite imagery. As a consequence, the present state of global urban mapping is much more modest, with most products simply attempting to depict the outline of the developed area at or near 1-km resolution.

Among the data sources regarded as most promising for global urban mapping are the observations of nighttime lights. The widespread use of such lighting is a relatively recent phenomenon, tracing its roots back to the electric light bulb commercialized by Thomas Edison in the early 1880s. Artificial lighting has emerged as one of the hallmarks of modern development and provides a unique attribute for identifying the presence of development or human activity that can be sensed remotely. Although there are some cultural variations in the quantity and quality of lighting in various countries, there is a remarkable level of similarity in lighting technology around the world. Thus, the remote sensing of artificial lighting is viewed as an accurate, economical, and unambiguous way to map the global distribution and density of developed areas.

The only satellite sensor currently collecting global low-light imaging data suitable for mapping urban lighting is the U.S. Air Force Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS). The DMSP OLS was designed to collect global cloud imagery using a pair of broad spectral bands placed in the visible and thermal. The DMSP satellites are flown in polar orbits and each collects 14 orbits per day. With a 3000-km swath width, each OLS is capable of collecting a complete set of images of the Earth twice a day. At night, the visible band signal is intensified with a photomultiplier tube (PMT) to enable the detection of moonlit clouds. The boost in gain enables the detection of lights present at the Earth’s surface. Most of the lights are from human settlements (cities and towns) and fires, which are ephemeral. Gas flares are also detected and can easily be identified when they are offshore or in isolated areas not impacted by urban lighting.

The DMSP-OLS has a number of favorable characteristics for global urban mapping including the potential for nightly global coverage and a manageable data volume. Over the years, a number of researchers have attempted to use DMSP-OLS nighttime lights as a representation of the urban geographic footprint (Doll et al., 2000; Ebener et al., 2005; Elvidge et al., 1997, 1999, 2004; Foster, 1983; Gallo et al.,
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1995, 2004; Imhoff et al., 1997; Lo, 2002; Sutton and Costanza, 2002; Sutton, 2003; Sutton et al., 2007; Welch, 1980). These studies revealed that the OLS-derived lighting features are substantially larger than the lighting sources present on the ground and that local economic conditions impact the detection and brightness of satellite observed lighting. Both of these effects detract from the value of the data in mapping urban footprints. On the other hand, it is possible that nighttime lights depict the spatial patterns of global resource consumption and economic activity more clearly than any other available satellite data source. In this chapter, we examine three types of global urban product types developed based on DMSP-OLS nighttime lights and discuss possible improvements in the remote sensing of nocturnal lighting.

6.2 DENSITY OF CONSTRUCTED SURFACES

Human beings around the world build, use, and maintain constructed impervious surfaces for shelter, transportation, and commerce. Constructed surfaces include roads, buildings, sidewalks, driveways, and parking lots. Collectively, these represent one of the primary anthropogenic modifications of the environment. Expansion in population numbers and economies combined with the popular use of automobiles has led to the sprawl of development and a wide proliferation of constructed impervious surfaces. It is anticipated that the worldwide pattern of sprawl development will continue in the coming decades in response to both population growth and improvement in living standards.

Constructed impervious surfaces can be viewed as hydrological and ecological disturbances. However, constructed surfaces are different from most other types of disturbances in that recovery is arrested through the use of materials that are resistant to decay and are actively maintained. The same characteristics that make impervious surfaces ideal for use in construction produce a series of effects on the environment (Schueler, 1994). Impervious surfaces alter sensible and latent heat fluxes, causing urban heat islands (Changnon, 1992). In heavily vegetated areas, the proliferation of impervious surface area (ISA) reduces the sequestration of carbon from the atmosphere (Milesi et al., 2003). ISA alters the character of watersheds by increasing the frequency and magnitude of surface runoff pulses (Booth, 1991). Watershed effects of ISA begin to be detectable once 10% of the surface is covered by impervious surfaces, altering the shape of stream channels, raising water temperatures, and sweeping urban pollutants into aquatic environments (Beach, 2002; Carlson, 2007). Hydrologic consequences of ISA include increased flooding, reductions in ground water recharge, and reductions in surface water quality.

Spatial grids depicting the density of constructed surfaces are typically in units of percent cover and are widely used in hydrologic modeling and flood prediction. These grids are distinctly different from traditional urban land use products that report classes such as commercial/industrial, high-density residential, and low-density residential. For applications such as hydrologic modeling, land use data are not nearly as useful as constructed surface density grids.

There are three primary remote sensing approaches to estimating the density of constructed surfaces (Slonecker et al., 2001; Weng, 2007). The first approach is to
map constructed areas using high spatial resolution imagery (Goetz et al., 2003; Yang et al., 2003; Slonecker, and Tilley, 2004). Typically, ISA products derived from high spatial resolution imagery cover small areas and to date, there has not been a standardization of methods that would facilitate the merger of products generated by diverse organizations. The second approach is to use moderate spatial resolution multispectral data (e.g., Landsat) to estimate the density of ISA. Such a product was recently produced by the U.S. Geological Survey using Landsat 7 data from the early 2000s (Yang et al., 2003; Crane et al., 2005). This product has 30-m resolution and a combination of spectral and spatial methods to estimate the density of ISA. A subsample of high spatial resolution imagery was used to establish the methodology and to provide an accuracy assessment. The third approach is to use indicators to estimate the density of ISA. As an example, Stankowski (1972) proposed the estimation of ISA based on population density. Another indirect method is the estimation of ISA based on coverage coefficients developed for standard land cover classes, such as low-density residential, high-density residential, commercial/industrial (Jennings et al., 2004).

We have used nighttime lights to estimate the density of constructed surfaces. Elvidge et al. (2004) pioneered this approach, producing a 1-km² grid of constructed surface densities for the conterminous USA using nighttime lights, street, and road density (from the U.S. Census Bureau), and three urban land cover classes from the early 1990s (Vogelmann et al., 2001). Subsequently, Elvidge et al. (2007a) produced a global density grid of constructed surfaces using nighttime lights and population count from the U.S. Department of Energy Landsat data (Dobson et al., 2000; Bhaduri et al., 2002). These data products are available at http://www.ngdc.noaa.gov/dmsp/download_global_isa.html.

The 20 leading countries in terms of total ISA are shown in Table 6.1. Also listed is the quantity of ISA per person in square meters. At the bottom of the table, we list the total ISA for all countries and the average amount of ISA found per person worldwide. Clearly, the countries that measure high on total ISA are either large in areal extent and/or total population, or have high levels of economic development.

The countries with particularly high values of ISA per person according to our estimation are almost universally affluent (United States, Canada, Norway, Sweden, Finland, Spain, France, Bahrain, Brunei, Qatar, and the United Arab Emirates). With the exception of Brunei, these countries cluster in the northern hemisphere (Figure 6.1). It is interesting to note that Japan and Mexico both score at lower identical levels (114 m² of ISA per person). Japan’s moderate level of ISA (relative to their GDP per capita) can be attributed to the topographic and agricultural constraints on development present in that country.

The total ISA of the world is estimated to be 579,703 km². This is nearly the same size as the country of Kenya (584,659 km²), and larger than Spain (505,735 km²) or France (546,962 km²). The country with the most ISA is China (87,182 km²), followed closely by the United States (83,881 km²) and India (81,221 km²). China’s and India’s ISA footprints are population-driven, whereas the United States ISA footprint is more driven by affluence. Explorations of ISA per capita show generally expected patterns in that countries with high population densities (e.g., “big denominators”) show lower levels of ISA per capita. The global average of.
TABLE 6.1
Top 20 Countries in Terms of Constructed Surface Area

<table>
<thead>
<tr>
<th>Country</th>
<th>Constructed Surface Area (km²)</th>
<th>Population (Landscan 2004)</th>
<th>Constructed Surface Area per Person (m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>China</td>
<td>87,182</td>
<td>1,292,548,864</td>
<td>67.4</td>
</tr>
<tr>
<td>United States</td>
<td>83,881</td>
<td>282,575,328</td>
<td>296.8</td>
</tr>
<tr>
<td>India</td>
<td>81,221</td>
<td>1,058,349,824</td>
<td>76.7</td>
</tr>
<tr>
<td>Brazil</td>
<td>17,766</td>
<td>177,885,936</td>
<td>99.9</td>
</tr>
<tr>
<td>Russia</td>
<td>17,135</td>
<td>138,947,840</td>
<td>123.3</td>
</tr>
<tr>
<td>Indonesia</td>
<td>16,490</td>
<td>230,000,208</td>
<td>71.7</td>
</tr>
<tr>
<td>Japan</td>
<td>13,990</td>
<td>122,192,928</td>
<td>114.5</td>
</tr>
<tr>
<td>Mexico</td>
<td>11,854</td>
<td>103,608,488</td>
<td>114.4</td>
</tr>
<tr>
<td>Canada</td>
<td>11,295</td>
<td>32,022,750</td>
<td>352.7</td>
</tr>
<tr>
<td>Pakistan</td>
<td>10,666</td>
<td>150,465,168</td>
<td>70.9</td>
</tr>
<tr>
<td>France</td>
<td>9537</td>
<td>59,497,124</td>
<td>160.3</td>
</tr>
<tr>
<td>Bangladesh</td>
<td>8878</td>
<td>140,275,504</td>
<td>63.3</td>
</tr>
<tr>
<td>Germany</td>
<td>8500</td>
<td>82,406,312</td>
<td>103.1</td>
</tr>
<tr>
<td>Italy</td>
<td>8294</td>
<td>56,528,760</td>
<td>146.7</td>
</tr>
<tr>
<td>Nigeria</td>
<td>7668</td>
<td>125,118,728</td>
<td>61.3</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>7576</td>
<td>58,926,004</td>
<td>128.6</td>
</tr>
<tr>
<td>Spain</td>
<td>7037</td>
<td>39,481,976</td>
<td>178.2</td>
</tr>
<tr>
<td>Iran</td>
<td>6949</td>
<td>66,604,152</td>
<td>104.3</td>
</tr>
<tr>
<td>Vietnam</td>
<td>5981</td>
<td>81,249,416</td>
<td>73.6</td>
</tr>
<tr>
<td>Egypt</td>
<td>5745</td>
<td>75,240,640</td>
<td>76.4</td>
</tr>
<tr>
<td>Total Worldwide</td>
<td>579,703</td>
<td>6,245,732,591</td>
<td>93</td>
</tr>
</tbody>
</table>

FIGURE 6.1  Global distribution and density of constructed surfaces modeled from DMSP nighttime light and LandScan population count.
ISA per capita was estimated to be 93 m² per person. Examinations of ISA at the watershed level support ideas that there are both economic and demographic forces contributing to changes in the hydrologic and ecologic functioning of watersheds around the world.

The estimate of ISA is derived solely from the brightness of satellite observed nighttime lights and population count. Both of the input sources (nighttime lights and population count) are produced as 30 arc second grids (~1 km² resolution) and could potentially be updated on an annual basis. These two data sources are complementary in that the nighttime lights are generally brightest in the commercial and industrial areas — which are generally not well defined in the population count data. In areas where no lighting is detected the ISA estimate is based solely on population count. In the absence of detected lighting, the population count at which 100% ISA is reached is slightly more than 11,000 persons/km². At this density, each person is directly associated with 91 m² of ISA, nearly the global average of 93 m² per person.

As the world economy and population expands it can be projected with confidence that the constructed surfaces of the Earth will expand significantly. For the moment, this product stands as the only global ISA grid. We offer it as a pathfinder, recognizing that the mapping of constructed surface at both the global and local scale will continue to improve over time.

### 6.3 GLOBAL POVERTY MAP

During our work with nighttime lights and the Landscan population count data, we had the occasion to overlay the two datasets as a color composite image. In this image, it is possible to see areas devoid of satellite detected lighting in the densely populated belts of poverty in China, India, and across Africa. Using Europe and the United States as visual reference, it is also possible to see regions where the satellite-detected lighting is dim relative to the population numbers. We developed the notion of using the quantity of lighting per person as an indicator of poverty levels. The concept is that in prosperous regions of the world there is no shortage in lighting. The quantity of lighting per person declines as poverty rates increase. Our assumption is that the satellite will be unable to detect lighting in the areas with the most extreme poverty levels.

Poverty has emerged as one of the chronic dilemmas facing civilization during the 21st century. Based on data from the World Development Indicators (World Bank, 2006), approximately 42% or 2.6 billion people live in poverty. Poverty is the general term describing living conditions that are detrimental to health, comfort, and economic development. There are different forms of poverty, such as inadequate supply or quality of food, water, sanitation, housing, clothing, schools, and medical services. In locations where poverty levels are high, there is typically a convergence of inadequacies across several of these areas. Widely noted consequences of poverty include higher infant mortality, shorter life spans, and lower literacy rates. Poverty is also closely associated with environmental degradation (Snel, 2004). The United Nations Millennium Development Goals includes a 50% reduction in extreme poverty by the end of 2015. Economic analyses (Sachs, 2005) indicate that eliminating poverty is a realistic objective.
The primary source for statistics on global poverty is the World Bank, which has collected and distributed national-level data on poverty levels since 1990. Their methods are based on the analysis of household surveys conducted in almost 100 countries. Survey questions cover sources of income, consumption, expenditures, and numbers of individuals making up the household. Most surveys are conducted by government employees. Two styles of poverty data are produced — national poverty line data and international poverty line data. Individual countries establish their own poverty line for the national data. Differing standards in defining poverty make pooling the national poverty line data problematic. More recently, purchasing power parity has been introduced into the formulation of international poverty line data, which is specified in terms of the number of individuals living on either $1 or $2 per day (Figure 6.2).

There are a number of problems recognized with the World Bank poverty line data: not all countries conduct the surveys, the currently available data were derived from surveys spanning 1988 through 2004, and the survey repeat cycle is uncertain. The intercomparability of the estimates is uncertain due to difficulties in reconciling consumption and income data, plus discrepancies in the purchasing power parity estimates for individual countries (Karshenas, 2004). It is also possible for governments to influence the outcome of the surveys, because they design the questions, select the areas for survey, and conduct the interviews. The use of the $1 and $2 per day standards for the international poverty line data is not applicable to prosperous countries such as the United States, where 12% of the population is listed in poverty (De Navas-Walt et al., 2005).

Poverty maps have emerged as important tools for targeting aid and development resources (Sachs, 2000; Sachs et al., 2001; Henninger and Snel, 2002; CIRESIN, 2006). Poverty maps traditionally depict a single measure or index value for an entire administrative unit, such as country or state. Spatially disaggregated global maps of the numbers of individuals living in poverty, based on a consistent definition of the poverty line would be extremely useful for targeting of efforts to reduce poverty (Hentschel and Lanjouw, 1998). Part of the value of spatially disaggregated data is that they can be aggregated to multiple levels: national, state, substate, or

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FIGURE 6.2  Map of poverty levels for countries reporting international poverty line data (percent of population living on $2 per day or less) from the World Development Indicators 2006. Note that a number of countries have no data reported and that the $2 per day poverty line is not applicable to developed countries.
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municipal. If spatially disaggregated poverty maps could be updated on an annual or semiannual basis, they could be used to track the effectiveness of poverty reduction efforts in specific localities and the consequences of natural disasters, epidemics, or conflicts.

Two spatially disaggregated data sources have been combined to form a global poverty index (PI): LandScan population counts and DMSP nighttime lights. We defined a PI as the LandScan 2004 population count divided by the average visible band digital number from the lights (Figure 6.3). In areas where population is present but no lights were detected, the full population count is passed to the index.

**FIGURE 6.3** Poverty index calculated by dividing the LandScan 2004 population count by the average digital number of the DMSP satellite F15 nighttime lights from 2003.

**FIGURE 6.4** Calibration of the Normalized Poverty Index (NPI) for estimation of poverty levels.
A calibration for estimating the number of people living in poverty was developed based on the World Development Indicators 2006 national level estimates for the percentage of people living on $2 or less per day. To establish the calibration, the sum of the PI values was extracted for each country. This sum was then divided by the total population count and multiplied by 100.0 to form a normalized poverty index (NPI). The NPI was then regressed to the percentage of the population living on $2 per day or less (Figure 6.4).

The calibration from Figure 6.4 was applied to the NPI grid to estimate the poverty level in each grid cell and then multiplied by the LandScan population grid to yield an estimate of the poverty count. The gridded product is available at http://www.ngdc.noaa.gov/dmsp/download_poverty.html. The calibration was also applied to national level NPI and LandScan population counts to yield spatially aggregated poverty estimates. This was done for 232 countries to generate national poverty levels and poverty counts, which are available in spreadsheet form at the Web site. Among the 80 countries having populations greater than 10 million, those having poverty rate estimates greater than 80% are Ethiopia, Burkina Faso, Madagascar, Cambodia, Uganda, Tanzania, and Niger. Those having estimated poverty rates less than 10% include Taiwan, South Korea, Egypt, Saudi Arabia, Japan, Belgium, Netherlands, Italy, United Kingdom, and the United States.

The procedure used to generate the national level poverty estimates was then applied at subnational level for 2543 administrative units having LandScan population values above zero. These results are presented graphically in Figure 6.5. Many of the patterns present within individual countries match expected results, with lower poverty levels in the more prosperous areas. For instance, coastal China has lower poverty rates than the interior area, northeastern India has higher poverty rates than western and southern India, and the prosperous Sao Paulo region has lower poverty rates than other parts of Brazil. The effects of lighting from gas flares, which reduce the poverty estimates, can be observed in coastal Nigeria. A comparison of the estimated poverty rates in the United States versus measured rates reported for 2004 by De Navas-Walt et al. (2005) revealed an RMSE of 4.22%.

**FIGURE 6.5** (See color insert following page 324.) Map of poverty levels for 2,543 subnational administrative units estimated based on the satellite data–derived poverty index.
6.4 ESTIMATION OF ECOLOGICAL FOOTPRINTS

We have explored the potential of using satellite-based estimates of a constructed area as a spatially disaggregated proxy for the human ecological footprint. Recently, the National Geophysical Data Center produced the first global grid of constructed area densities based on satellite-derived nighttime lights and population count data (Elvidge et al., 2007a). We have preliminary evidence (presented below) that spatial variation in the density of constructed area strongly correlates with the spatial variation in human ecological footprints.

The ecological footprint is a well-established resource accounting tool that estimates how much biologically productive land and water area an individual or a geographically defined population uses to produce the resources it consumes and to absorb the wastes it generates based on prevailing technology and resource management practices (Wackernagel and Rees, 1996). Ecological footprint calculations have emerged as a valuable means to communicate and understand human impacts on the natural systems upon which we depend. They are also useful in modeling the longer-term impacts of human consumption — both on natural systems and society.

One of the principles in calculating ecological footprints is that populations utilize widely distributed resources. This is a key consideration for urban populations because the land used to generate their food, fiber, and wood are widely distributed and could be halfway around the world. Similarly, the absorption of CO₂ produced by fossil fuel is widely distributed. Another principle used in the calculation of ecological footprints is that it is not necessary to pinpoint the location that produces the resources used by a population. Based on this consumption, the quantity of land or water surface required to generate that quantity of resource is calculated in terms of a normalized standard for biological productivity.

The Ecological Footprint’s widely used normalized standard measurement unit is global hectares (GHA), defined as a biologically productive hectare with world average productivity. Kitzes et al. (2007) estimate that in 2003 the Earth made available 11.2 billion GHA while maintaining humanity’s consumption depended on 14.1 billion GHA. Thus, humanity’s resource consumption in 2003 was rated at 25% more than the Earth was able to produce in the same year. Another way to look at this number is that it took the Earth 15 months to produce the resources used by humanity in a 12-month period. When consumption exceeds production, the difference between the two numbers is made up by liquidating the Earth’s ecological stores and the accumulation of waste products such as CO₂ in the atmosphere. These results and the ecological implications appeared in a recent report issued by WWF International (2006).

While a growing number of organizations are producing estimates of ecological footprints, the Global Footprint Network (GFN) has emerged as the premier organization in establishing and updating the standards used and produces the most widely cited national and global ecological footprint estimates. The GFN assembles data from a wide range of sources to produce National Footprint Accounts, which record the resources consumed, CO₂ emissions, and calculations of the land and water areas that need to produce the resources and absorb the CO₂. The data sources and modeling continue to evolve under the auspices of a standards
committee. Their most recent report (Ecological Footprint Standards 2006) is available at http://www.footprintstandards.org/. Each year, national footprint accounts are updated to track the consumption of crop products, fibers, livestock, fish, timber, fuel wood, and CO₂ produced. From these values, the model calculates the GHA utilization. The surface cover types that are tracked by national footprint accounts include cropland, grazing land, fishing grounds, forest, built-up land, and “carbon land.” Land cover extents are drawn from multiple sources including CORINE, Global Agro-Ecological Zones, GLC 2000, and World Conservation Monitoring Center. Of these cover types, built-up land area estimates may be the least reliable data set, and weakest for global comparison (Kitzes et al., 2007).

By dividing the constructed area by population count, it is possible to produce a disaggregated grid estimating the constructed area per person. By aggregating these values, it is possible to estimate the constructed area per person at a variety of levels — including national and subnational administrative units. Figure 6.6 shows the national level constructed area per person (in square meters) versus the ecological footprint per person (in GHA) for 149 countries (from the GFN). For constructed area per person values in the 30- to 60-m² range, the ecological footprint is set at about 1 GHA. Beyond 60 m², the ecological footprint increases along with the constructed area per person values in a largely linear manner.

The constructed area data may be used to improve either the quality or the spatial resolution of ecological footprints: (1) by using the quantity of built-up land as an input into the National Footprint Account estimation models. The satellite derived constructed area data can be used as the input for built-up lands. (2) As Figure 6.6 shows, it is possible to estimate national level ecological footprints based on the constructed area per person metric. This relationship can be used to estimate and evaluate the ecological footprints for the 80+ countries and small islands (e.g., Brunei, Oman, Seychelles, Aruba) not covered by the GFN estimates, and (3) the subnational estimation of ecological footprints can also be made by working from the highly refined national level estimates and the disaggregated constructed area/person grid.

**FIGURE 6.6** Constructed area per person versus ecological footprint per person for 149 countries.
6.5 CONCLUSION

Global urban mapping has, in most cases, been constrained to simple delineations of urban or developed areas. In this chapter, we have presented concepts for three types of global maps that characterize the density, living conditions, and resource consumption levels within human settlements on spatially disaggregated grids.

The estimate of ISA has been derived solely from the brightness of satellite-observed nighttime lights and the population count has been derived from the Landscan population grid. The ISA per capita revealed that countries with high population densities such as China and India had lower levels of ISA per capita.

A global map of poverty levels has been produced using a combination of four types of satellite data [DMSP lights, moderate resolution imaging spectroradiometer (MODIS) land cover, shuttle radar topography mission (SRTM) topography, and controlled image base (CIB)]. The MODIS, SRTM, and CIB data were used as inputs (along with census data) into a global population grid. DMSP lights were used as a measure of economic activity. The PI used to estimate poverty levels is calculated by dividing population count by the brightness of the nighttime lights. A calibration was developed using national-level poverty levels reported by the World Development Indicators 2006. The resulting estimate for the number of people living in poverty is 2.3 billion, consistent with the 2.6 billion estimated by the World Bank (2006).

The third style of global urban mapping that we have explored is focused on resource consumption. Although the OLS is remarkable for its detection of dim lighting, it is clear that the quality of global urban mapping products could be improved through the detection of even dimmer lighting with improvements in spatial resolution. The full suite of shortcomings of the OLS data for urban mapping include: (1) coarse spatial resolution (2.7-km ground sample distance), (2) lack of onboard calibration, (3) lack of systematic recording of in-flight gain changes, (4) limited dynamic range, (5) 6-bit quantization, (6) signal saturation in urban centers resulting from standard operation at the high gain setting, (7) lack of a thermal band suitable for fire detection, (8) limited data recording and download capabilities (most OLS data are averaged on-board to enable download of global coverage), (9) lack of a well-characterized point spread function (PSF), (10) lack of a well-characterized field of view, and (11) lack of multiple spectral bands for discriminating lighting types.

Several of the observational shortcomings of the OLS will be addressed by the low-light imaging data that will be acquired with the Visible/Infrared Imaging Radiometer Suite (VIIRS), which will fly on the National Polar Orbiting Environmental Satellite System (NPOESS) in the next decade. The VIIRS low-light imaging sensor will continue to acquire nightly global data, but will have onboard calibration and at higher spatial resolution (0.8 km) than the OLS. Thus, it can be expected that poverty assessments made with VIIRS data will be of higher quality than those that can be achieved with the OLS. The VIIRS, however, is not designed with the objective of sensing nighttime lights. Rather, it has the objective of nighttime visible band imaging of moonlit clouds — the same mission objective of the OLS low-light imaging. The VIIRS low-light imaging spatial resolution will be too coarse to permit the observation of key nighttime lighting features within human settlements. Also, the spectral band to be used for the low-light imaging is not tailored for nighttime lighting.
In total, OLS lighting was not detected for 1.68 billion people. Although the OLS is remarkable for its detection of dim lighting, it is clear that the quality of the PI could be improved through the detection of even dimmer lighting. The VIIRS instrument is designed to match the detection limits achieved by the OLS. In addition, both OLS and VIIRS will only acquire low-light imaging data in a single broad visible/near-infrared band. There is spectral information on the type of lighting, and changes in the type of lighting could be quite useful for improving the quality of poverty estimates. The final area where a substantial improvement in low-light imaging could be envisioned is in spatial resolution. On the basis of recent simulations made with high spatial resolution airborne camera imagery of nighttime lights, nighttime photography from the International Space Station and ground-based spectral measurements, Elvidge et al. (2007b, 2007c) developed the Nightsat mission concept. To be effective in delineating primary nighttime lighting patterns, Nightsat low-light imaging data should not exceed 50- to 100-m spatial resolution and achieve minimal detectable radiances in the range of $2.5 \times 10^{-8}$ $\text{W cm}^{-2} \text{sr}^{-1} \text{µm}^{-1}$. Although panchromatic low-light imaging data would be useful, multispectral low-lighting imaging data acquired with three to five spectral bands would enable more quantitative applications and enable the detection of lighting type conversions.

Cloud and fire screening of the low-light imaging data would be accomplished using simultaneously acquired thermal band data. The thermal band data could come from VIIRS if Nightsat were flown on an NPOESS satellite. The system would use a combination of methods to produce radiance-calibrated data. Geolocation accuracy would be 50 m, comparable to that of Landsat. The system objective would be to collect a sufficient quantity of imagery to construct annual global cloud-free composites of nighttime lights. A near-Sun-synchronous polar orbit, with an early evening overpass, would provide temporal consistency important for change detection (Elvidge et al., 2007b, 2007c).

Nightsat system would enable a wide range of social, economic, and biological applications where there is currently a dearth of systematically collected, unbiased, global data. Nightsat data would provide important constraints and inputs for the spatial modeling of human population growth and distribution, land use, rates of development, anthropogenic emissions to the atmosphere, and independent estimation of economic indices. In addition, Nightsat data would be used to model and understand human impacts on the environment such as the proliferation of impervious surface area, nonpoint sources of aquatic pollution, habitat fragmentation, and the direct effects of nocturnal lighting on night environment, human health, security, and the visibility of stars. Moderate-resolution low-light imaging sensor data would be an important complement to the mapping capacity of moderate resolution daytime imaging sensors such as Aster and Landsat because it would provide an unambiguous indication of the presence of development and growth in development. Nightsat data would also be useful for calibrating and validating coarser resolution low-light imaging data acquired with the OLS and VIIRS sensors (Elvidge et al., 2007b, 2007c).

Although urban areas occupy only a small fraction of the Earth’s surface, urbanization has risen to become one of the driving forces altering the Earth environment. Urban areas are the focal points for the consumption of food, water, and energy. They are likewise the focal points for both air and water pollution. Most of the agricultural,
fisheries, and resource exploitation activities constituting the balance of human impacts on the environment are driven by the consumption occurring in urban areas. The widespread use of impervious construction materials results in vastly increased surface runoff, which alters the stream flow and biodiversity. Urban areas tend to be built on flat, low-lying areas, often replacing wetlands. Although urban areas cover only a small percentage of the Earth's surface, their influence is enormous.

In the coming decades, urbanization will have a profound effect on the biological, chemical, and climate systems of our planet, both at local and at global scales. Urban areas are the largest sources of anthropogenic greenhouse gas emissions, and major sources of aerosols and water pollution. Urban expansion results in losses of agricultural lands and the fragmentation of wildlife habitats. Urban areas will expand dramatically as human population numbers are expected to double in the next 60–70 years. The increased urban demands for energy, food, and water will tax natural systems.

In no small measure, the activities concentrated in urban areas will determine the future habitability of our planet as a home for humankind and other species. There are legitimate questions regarding the sustainability of the current pattern of urbanization in the face of anticipated population and economic growth. Over time, urban areas may evolve to become more compact, energy-efficient, and less polluting, exerting a smaller footprint on the environment. In the interim, remotely sensed data provide one of the best sources of information on how urban areas are changing through time and how they affect the environment.

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Global Urban Mapping Based on Nighttime Lights


COLOR FIGURE 6.5  Map of poverty levels for 2,543 sub-national administrative units estimated based on the satellite data–derived poverty index.

COLOR FIGURE 8.1  Urban extents and rural settlements in the Nile Delta (FAO-PMUR), 2000.