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A review of regional science applications of satellite remote sensing in urban settings

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ABSTRACT

This paper reviews the potential applications of satellite remote sensing to regional science research in urban settings. Regional science is the study of social problems that have a spatial dimension. The availability of satellite remote sensing data has increased significantly in the last two decades, and these data constitute a useful data source for mapping the composition of urban settings and analyzing changes over time. The increasing spatial resolution of commercial satellite imagery has influenced the emergence of new research and applications of regional science in urban settlements because it is now possible to identify individual objects of the urban fabric. The most common applications found in the literature are the detection of urban deprivation hot spots, quality of life index assessment, urban growth analysis, house value estimation, urban population estimation and urban social vulnerability assessment. The satellite remote sensing imagery used in these applications has medium, high or very high spatial resolution, such as images from Landsat MSS, Landsat TM and ETM+, SPOT, ASTER, IRS, Ikonos and QuickBird. Consistent relationships between socio-economic variables derived from censuses and field surveys and proxy variables of vegetation coverage measured from satellite remote sensing data have been found in several cities in the US. Different approaches and techniques have been applied successfully around the world, but local research is always needed to account for the unique elements of each place. Spectral mixture analysis, object-oriented classifications and image texture measures are some of the techniques of image processing that have been implemented with good results. Many regional scientists remain skeptical that satellite remote sensing will produce useful information for their work. More local research is needed to demonstrate the real potential and utility of satellite remote sensing for regional science in urban environments.

Contents

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1. Introduction

Regional science can be defined as a discipline concerned with the study of social, economic, political and behavioral phenomena that have regional or spatial dimensions, using combinations of analytical and empirical research methods (Isard, 1975; Isserman, 2004). The spatial aspect involved in regional science research is what makes remote sensing appealing for extracting spatial data that can be related to the phenomena under analysis. Aerial photography has been used as input data in regional science applications in urban settlements since the late 1950s. The use of this type of remotely sensed data is supported by the hypothesis that the surface appearance of a settlement is the result of the human population's social and cultural behavior and interaction with the environment, which leave their mark on the landscape. Remotely sensed data from satellites can also be used to measure the context of social phenomena, to gather additional contextual data on the environment in which people live, and to measure the environmental consequences of social processes (Rindfuss & Stern, 1998, chap. 1). Lo and Faber (1997) state that it is through greenness (i.e., the amount of green vegetation) that remotely sensed environmental data can be combined with socio-economic census data and list early examples of the use of remotely sensed data for the social analysis of cities. Topics covered in those early studies included social structure and residential desirability (Green, 1957; Monier & Green, 1957), urban poverty (Metivier & McCoy, 1971; Mumbower & Donoghue, 1967), and urban quality of life (Weber & Hirsch, 1992). Mullens and Senger (1969) and Miller and Winer (1984) are also pioneering works that reported relationships between aerial remotely sensed data and demographic, social and economic characteristics of neighborhoods in a city. The application of empirical models to estimate biophysical, demographic and socio-economic variables has been reported as one of the top five recurrent research themes in applications of remote sensing to urban environments (Phinn, Stanford, Scarth, Murray, & Shyy, 2002).

The availability of remote-sensed data has increased significantly as its costs have decreased in the last two decades. These data provide a useful method for mapping the compositions of cities and analyzing changes over time (Weng & Quattrochi, 2006, chap. 4). The unique characteristics of remotely sensed data, such as repeat cycle and wide area coverage, provide means for exploring and testing hypotheses and models about urban areas and for constructing new theories that can help policy makers to analyze and respond to problems that involve urbanization processes (Rashed, Weeks, Stow, & Fugate, 2005). The increasing spatial resolution of commercial satellite imagery has been crucial to the emergence of new studies and applications related to urban settlements because it is now possible to identify the individual objects of the urban fabric, such as individual buildings and details of road networks and open spaces (Sliuzas, Kuffer, & Masser, 2010, chap. 5).[1]

The increased availability of high-resolution remote sensing data can also be considered a response to the growing need for high spatial and temporal resolution data on urban agglomerations.[2] The worlds population is now mostly urban, and information about urban settings, their internal compositions and their dynamics is very important to the preservation of certain standards of living (Phinn et al., 2002). Processes taking place in urban areas are among the main drivers of land change on local to global scales (Herold, 2009, chap. 2). According to the United Nations, the 20th century witnessed the urbanization of the world's population, with the percentage of urban dwellers increasing from 13% in 1990 to 49% in 2005, and this figure is expected to grow to 60% in 2030 (United Nations, 2007, 2008). In 2007, the populations of the Americas, Europe and Oceania were over 70% urban, and those of Asia and Africa were approximately 40% urban. Every year, a larger absolute number of persons is added to the world's urban population; this situation is believed to be more significant in the less developed regions of the world, whose population growth in urban areas is projected to account for almost all of the world population growth between 2005 and 2030 (United Nations, 2008). This situation brings attention to the existing inequities within urban settings. In developing countries, variations in poverty and health within urban areas can be larger than the differences between urban and rural settlements (Montgomery & Hewett, 2005; Stow, Lopez, Lippitt, Hinton, & Weeks, 2007); hence, urban settings need to be studied and monitored at very high spatial and temporal resolutions.

Remote sensing is widely known among urban planners, city planners and policy makers as a useful tool for extracting biophysical information about the urban environment, including land-cover and land-use mapping, urban morphology description and analysis, vegetation distribution and characterization, hydrography and disaster relief. This tool is also widely used in the field of natural resource exploration and management. However, little is known about the detection of the subtle relationships between the physical appearance of the urban landscape and the socio-economic conditions of the population. The data that are currently available from Earth observation systems present an opportunity to collect information about urban settlements at several scales and on several dimensions (Netzband & Jürgens, 2010, chap. 1), and urban population growth and problems will increase in relevance in the coming decades (Sembler, 2006; Stow et al., 2007; Weeks, Getis, Hill, Gadalla, & Rashed, 2004). Therefore, it is important to demonstrate how remote sensing tools can contribute useful information to the study of cities and urban settlements.

The two most recent reviews of the use of remote sensing imagery in research related to socio-economic issues in urban settings are Jensen and Cowen (1999) and Miller and Small (2003). Jensen and Cowen (1999) focused on the technical requirements of remotely sensed data to extract information related to urban and suburban infrastructure and socio-economic attributes. They reviewed only population estimation and quality of life indicators. They stated that one of the most important requirements for detecting those features of interest in the image is the spatial resolution of the remotely sensed data. In the last decade, we have witnessed a large increase in the use of very high-resolution space-borne sensors and programs and the introduction of "government-wide" data purchases, which, in turn, have resulted in an increase in the availability of imagery at very high spatial resolutions. Thus, the spatial resolution requirement has been met, and the temporal resolution issue is becoming more of a budget issue than a technical one. These technological advancements have created a clear opportunity for the regional science community to begin to explore and use remotely sensed data in their daily work.

Miller and Small (2003) reviewed the potential applications of remote sensing in urban environmental research and policy. They showed that remotely sensed data could be used to obtain internally consistent measurements of physical properties at a lower cost than that of in situ measurements. The use of remote sensing data is usually more suitable for measuring and monitoring urban environmental conditions than for urban planning purposes because in the latter case, governmental and private sector data are more easily obtained. However, new developments and applications have taken advantage of the consistency of the remote sensing data to study the spatio-temporal dynamics of urbanization,

[1] The complete Landsat archive is freely available through the University of Marylands Global Land Cover Facility (GLCF) and United States Geological Survey (USGS) Internet sites.

[2] High-resolution population data in gridded format for 50 metropolitan statistical areas (MSAs) in the US have recently been released into the public domain.

suburbanization, land-cover or land-use changes, and urban morphology, which are topics of interest for urban planning (Griffiths, Hostert, Gruebner, & der Linden, 2010; Lu & Weng, 2004; Rashed, Weeks, Gadalla, & Hill, 2001; Rashed et al., 2005; Taubenböck, Wegmann, Roth, Mehl, & Dech, 2009; Yin, Stewart, Bullard, & MacLachlan, 2005). Since Miller and Small (2003), advances in remote sensing applications for regional science in urban settlements have occurred in the areas of crime and nighttime lighting relationships (Weeks, 2003, chap. 16); urban land cover and socio-economic change relationships (Mennis & Liu, 2005); population density estimation (Liu, Clarke, & Herold, 2006); house value modeling (Yu & Wu, 2006); socio-economic status mapping (Avelar, Zah, & Tavares-Correa, 2009; Stow et al., 2007); population estimation in informal settlements (Galeon, 2008); social vulnerability to landslides (Ebert & Kerle, 2008); land surface temperature relationship with socio-economic parameters (Rajasekar & Weng, 2009); urban morphology and socio-economic parameters (Taubenböck, Wegmann, et al., 2009); and spatio-temporal analysis of urban sprawl (Taubenböck, Wurm, et al., 2009). Multidisciplinary work is often used in these applications, with experts in remote sensing working together with architects, urban planners, sociologists and geographers to extract useful information from satellite imagery.

This paper reviews the potential of satellite remote sensing as a tool for regional scientists who are interested in intra-urban variations. It attempts to address the specific topic of satellite remote sensing tools applied to regional science research in urban settings. Through this work, policy and decision makers, geographers, economists, urban planners, and sociologists will be introduced to studies that have used remote sensing as input data to analyze issues of urban poverty, population dynamics, quality of life, and socio-economic status, among others.

The rest of this paper is organized as follows. Section 2 presents a brief summary of remote sensing data types and their main characteristics. Section 3 focuses on regional science applications in urban settings that use remote sensing as input data. A summary and conclusions are presented in Section 4.

2. Remote sensing data types

Remote sensing is used to gather information from distant objects by measuring the radiation that they reflect or emit. Remote sensing began with the development of photography in early 1800s by Louis Daguerre. The first aerial photographs were taken in the 1860s by Felix Tournachon in France using a camera mounted on a balloon (de Sherbinin et al., 2002; Short, 2010). Cameras mounted on planes were first used for military reconnaissance in World War I and II. The military need for separating real vegetation from camouflage resulted in the development of remote sensing beyond the human eye's visible range with the introduction of infrared wavelength sensors. After World War II, civilian applications of airborne remote sensing were developed for hazard mapping, vegetation mapping and planning. Space-based remote sensing started in the late 1950s with the launch of the first military intelligence satellite. A few years later, the first US meteorological satellite was launched, which was designed to aid in the production of generalized weather maps. The first Earth observation satellite was launched a decade later in 1972 and is known today as Landsat (de Sherbinin et al., 2002).

Although aerial photography has been used as a tool for urban analysis since the late 1950s, the focus of remote sensing research has shifted to the use of imagery acquired by Earth-orbiting satellite sensors as a result of the lower costs and frequency of updates of this imagery (Donnay, Barnsley, & Longley, 2001). The earliest launched satellites are known as first-generation sensors and were able to produce digital images of the Earth's surface with relatively moderate spatial resolution (i.e., 80 m of pixel size for Landsat MSS – Multispectral Scanning System) that were used primarily for regional scale studies. Second-generation satellites, such as Landsat Thematic Mapper and SPOT-HRV, increased the spatial resolution to 30 and 10 m, respectively, and enabled more detailed studies of urban systems. Third-generation satellites with very high spatial resolution (5–0.5 m), such as Ikonos and Quickbird, were launched in the last decade and have stimulated the development of newer detailed scale applications related to urban settlements, as anticipated by Donnay et al. (2001).

Sensors on board satellites used to gather data are of one of two types: active or passive. Both types collect electromagnetic radiation from the Earth's surface. Active sensors have their own energy source and emit a signal that travels through the atmosphere, reflects on the Earth's surface and returns to the sensor, which measures the signal's travel time and strength. Synthetic Aperture Radar (SAR) is an example of an active sensor that uses long-wavelength signals and thus can penetrate clouds or bad weather conditions. Passive sensors, also known as optic sensors, do not have their own energy source and usually record the radiation from the Sun that is reflected from the Earth's surface. Photographic cameras and multispectral scanners are passive sensors often used in satellite remote sensing.

The visible part of the electromagnetic spectrum is very small, and most satellite systems have been designed to be sensitive to other portions of the spectrum as well. This characteristic enables remote sensing analysts to see portions of the spectrum that the human eye cannot detect, thereby enhancing their ability to identify different surface materials. The spectral properties of a sensor are defined by the number, placement and width of bands within the electromagnetic spectrum that it is able to record. Panchromatic sensors measure reflected radiation in a single portion, usually located in the visible or infrared part of the electromagnetic spectrum, whereas multispectral sensors collect radiation in discrete parts of the spectrum, which are recorded as separate images called bands or channels. Today, most satellite remote sensing systems are composed of a panchromatic sensor and a multispectral sensor. Each sensor usually has a different spatial resolution, with the resolution of the panchromatic sensor being higher than that of the multispectral sensor.

Satellite systems can be placed in two types of orbits around the Earth. A geostationary orbit is obtained when the satellite orbits at a very high altitude and at the same speed as the Earth's rotation, thus remaining in a stationary position relative to the Earth and directed to the same portion of the Earth's surface. Satellites in this type of orbit are limited to a spatial resolution of 1–10 square kilometers and are used for weather and climate data collection and communications. A polar orbit is closer to the Earth's surface, between 700 and 1000 kilometers; passes through the poles of the Earth, describing a steep inclination relative to the Equator; and orbits in the opposite direction to the Earth's rotation. Satellites in this type of orbit can cycle around the Earth in 100–120 min, several times per day, and return to the same position after 2 weeks or more, allowing them to gather data on the same location over time. The time that elapses before a satellite returns to the same position is called the temporal resolution of the remote sensing system, and it has been defined as the capability for acquiring repetitive imagery over a certain time interval (Fugate, Tarnavsky, & Stow, 2010, chap. 7). Satellites in this type of orbit can obtain images with higher spatial resolution, ranging from 1 to 200 m (de Sherbinin et al., 2002).

Thus far, most regional science research in urban settings has used imagery from polar-orbiting satellites with passive sensors with medium, high or very high spatial resolution that provide good spectral resolution with multiple bands in the visible portion of the electromagnetic spectrum, at least one band located in the

Table 1
Most often used satellite remote sensing systems in regional science applications in urban settlements.

System	Spectral resolution	Spatial resolution (pixel size – meters)	Temporal resolution (days)	Archive since
Landsat MSS	3 bands visible 1 band infrared 1 band thermal infrared	80	18	1972
Landsat TM	3 Bands visible 3 Bands infrared 1 Band thermal infrared	30 – Visible and infrared 60 – Thermal infrared	16	1986
Landsat ETM+	3 Bands visible 3 Bands infrared 2 Bands thermal infrared 1 Band panchromatic	30 – Visible and infrared 60 – Thermal infrared 15 – Panchromatic	16	1999
SPOT 1 SPOT 2 SPOT 3	2 Bands visible 1 Band infrared 1 Band panchromatic	20 – Visible and infrared 10 – Panchromatic	26	1986
SPOT 4	2 Bands visible 2 Bands infrared 1 Band panchromatic	20 – Visible and infrared 10 – Panchromatic	2–3	1998
SPOT 5	2 Bands visible 2 Bands infrared 1 Band panchromatic	20 – Mid infrared 10 – Visible and near infrared 2.5–5 – Panchromatic	2–3	2002
ASTER	3 Bands visible 6 Bands infrared 5 Bands thermal infrared	15 – Visible 30 – Infrared 90 – Thermal infrared	16	1999
IRS-1C	2 Bands visible 2 Bands infrared 1 Band panchromatic	23.5 – Multispectral 5 – Panchromatic	5–24	1995
Ikonos	3 Bands visible 1 Band infrared	4 – Multispectral 1 – Panchromatic	1.5–2.9	1999
Quickbird	3 Bands visible 1 Band infrared 1 Band panchromatic	2.4 – Multispectral 0.6 – Panchromatic	1–3.5	2001

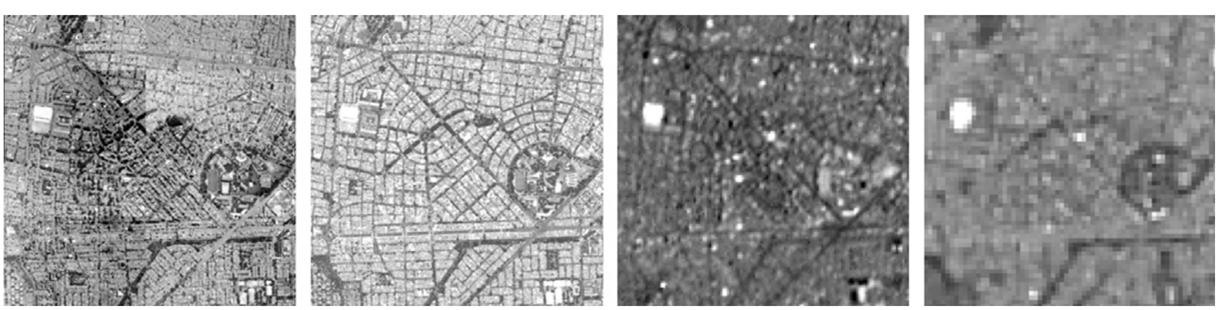

Fig. 1. Different images for an area of 2 km × 2 km of Medellin, Colombia. From left to right: digital orthophoto (pixel size: 0.125 m); Quickbird (0.6 m), Landsat ETM+ panchromatic band (15 m), and Landsat TM (30 m).

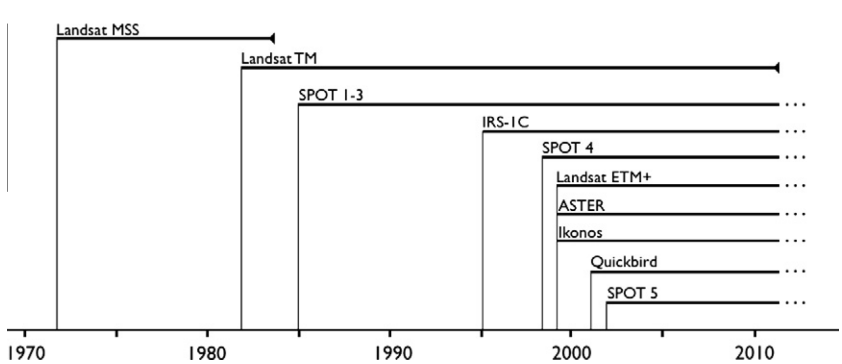

Fig. 2. Time scale of satellite systems listed in Table 1, modified after Fugate et al. (2010, chap. 7).

infrared portion of the spectrum and a panchromatic band. Table 1 lists the satellite remote sensing systems that are frequently used in urban regional science applications.[3] Fig. 1 illustrates the differences in spatial resolution of imagery from four different sensors by showing the same area of a city. Fig. 2 illustrates the lengths of archive of those satellite systems listed in Table 1.

3. Satellite remote sensing and regional science in urban settings

Although the variables of interest for regional scientists are not directly measured from the air, remote sensing can measure the context of social phenomena and their effects on the land surface (Rindfuss & Stern, 1998, chap. 1). The unique characteristics of remotely sensed data, such as wide area coverage and repeat cycle, provide a means for exploring and testing hypotheses and models about urban areas and for constructing new theories that can help in the analysis and response by policy makers of problems that involve urban processes (Rashed et al., 2005). The description of patterns of the urban landscape is a fundamental question in urban analysis (Rashed et al., 2001). This topic has been addressed through land-use/land-cover mapping, in which the landscape fabric is viewed as an arrangement of discrete pieces of homogeneous landscape, each one with a different type of land cover and function. In many urban applications, land-cover/land-use maps generated by the thematic classification of satellite images can be considered the starting point for further analyses (Donnay et al., 2001).

The relationships between urban land cover and other environmental factors and the variables that describe socio-economic conditions have been explored since the late 1950s with the use of aerial photography (Green, 1956, 1957). Research in the last three decades has explored the use of satellite remote sensing to characterize these relationships at a lower cost. In the urban environment, these relationships are based on the concept that the physical appearance of an urban settlement is a reflection of the society that created it and on the assumption that people living in urban areas with similar physical housing conditions will have similar social and demographic characteristics (Jain, 2008; Taubenböck, Wurm, et al., 2009).

Although Jensen and Cowen (1999) stated that the most important requirement for properly identifying urban socio-economic attributes using satellite remote sensing is the spatial resolution, several works have used satellite remote sensing at a medium resolution, such as Landsat MSS, TM and ETM+ imagery, to explore the relationships between land cover and socio-economic data (Emmanuel, 1997; Forster, 1983; Jenerette et al., 2007; Mennis, 2006). Because of the repeat cycles and length of archive of these medium spatial resolution systems, satellite imagery is available dating back to the 1970s, and the imagery is well suited to studying and monitoring urban changes and growth trends (Pham, Yamaguchi, & Bui, 2011; Rashed et al., 2005; Sabet, Ibrahim, & Kanaroglou, 2011; Van de Voorde, Jacquet, & Canters, 2011; Weng, 2012). Forster (1983) studied Landsat MSS images with pixel size of 80 m as a proxy for some socio-economic variables in Sydney, Australia. This study attempted to determine the reflectance of urban residential surfaces using Landsat MSS (multi-spectral scanner) data in an effort to develop equations to predict the percentages of different surfaces contributing to the total reflectance of a pixel and to determine the relationships between land-cover percentages and average residential home value as inputs to measure urban residential quality. The results were encouraging, and it was stated at that time that the potential of satellite remote sensing as a tool for urban analysis would be enhanced when newer satellite systems with higher spatial resolution became available.

Landsat and ASTER images have also been tested in research on relationships between urban land-cover and socio-economic data and their changes over a time span of decades in several cities in the US (Emmanuel, 1997; Jenerette et al., 2007; Mennis, 2006; Mennis & Liu, 2005; Rajasekar & Weng, 2009). Emmanuel (1997) found a significant and positive relationship between increases in urban vegetation measured from Landsat images from 1975 and 1992 and demographic factors associated with urban decay in Detroit, Michigan. It was concluded that vegetation trends in Detroit could be used as indicators of urban socio-economic changes. Mennis (2006) explored the relationship between urban vegetation and socio-economic conditions in Denver, Colorado. Land-cover data derived from aerial photography and vegetation data derived from Landsat ETM+ imagery were integrated using a geographic information system (GIS) with census data at the census-tract level. Multivariate statistics and choropleth mapping were used to explore relationships among variables, and association rule mining was used to explore other non-linear relationships.[4] The results from multivariate regression analyses showed that the amount of vegetation was positive correlated with a set of socio-economic variables that included median income, educational attainment, number of rooms and housing value and negative correlations with variables describing population density, commercial density and median year in which the housing unit was built. Results from association rule mining generally confirmed and improved the understanding of the multivariate regression results. These findings demonstrated the utility of integrating remote sensing and socio-economic data for the study of interactions of urban ecological and social systems. Mennis and Liu (2005) used similar techniques with GIS data to analyze urban land-cover and socio-economic changes in the same city from 1970 to 1990.

Jenerette et al. (2007) investigated regional relationships between surface temperature, vegetation conditions and human settlement patterns in the region of Phoenix, Arizona. Census data and a Landsat ETM+ image were used as inputs in this research. Surface temperature and vegetation data were derived from Landsat images, while social variables were derived from the 2000 US Census and included median household income, percent Hispanic population, median age of housing and population density. GIS was used to integrate these variables at the census tract level, and a path analysis multivariate model was used to measure the interaction between them. They found a strong correlation between vegetation and surface temperature, as expected. The correlations of temperature with median household income and with the percentage of Hispanic population were the strongest among all social variables. They also found that residential segregation of neighborhoods by socio-economic status influenced the vegetation and surface temperature patterns in the city.

Rajasekar and Weng (2009) used data mining techniques to explore the relationships between urban surface temperature and various biophysical and social parameters by integrating an ASTER satellite image and census data for Marion County, Indiana. The multispectral nature of ASTER images, with several spectral bands in the near infrared and thermal infrared parts of the spectrum, allowed the derivation of land surface temperature data, land-use/land-cover data and vegetation data (estimated with a scaled normalized difference vegetation index – NDVI). Population density was obtained from census data, and GIS land-use zoning and trans-

[3] For a detailed list of satellite platforms, the reader can review the ITC's database of Satellites and Sensors at http://www.itc.nl/research/products/sensordb/AllSatellites.aspx.

[4] For more information on this technique, see Zhang and Zhang (2002).

Table 2
Reported relationships among vegetation and socio-economic variables, (+) positive correlation, (−) negative correlation.

Reported in	Mennis (2006)	Lo (1997) and Lo and Faber (1997)	Jenerette et al. (2007)	Li and Weng (2007)	Jensen et al. (2004)
City	Denver, Colorado, Georgia	Athens-Clake	Phoenix, Arizona Indiana	Marion County, Indiana	Terre Haute, Indiana
Image	Landsat ETM+	Landsat TM	Landsat ETM+	Landsat ETM+	ASTER
Vegetation proxy	NDVI	NDVI	SAVI*	NDVI	LAI**
Method	Association rule mining	Principal Component Analysis	Path Analysis	Factor Analysis Regression Analysis	Regression Analysis
Socio-economic variable					
Residential density	+				
Commercial density	−				
Population density	−	−	−	−	−
Median income/per capita income/median household income	+	+	+	+	+
Percent minority/percent Hispanic	−		−		
Educational attainment	+	+		+	
Number of rooms	+			+	
Home year/year built	−		−		
Home value/median home value	+	+		+	+
Percent of urban use		−			
Percent of families under poverty level				−	
Unemployment rate				−	

portation buffer zone maps of Marion County were also included in the analysis. The model was developed using association rule mining and yielded interesting rules that may help researchers, planners and environmental managers to understand the relationships between biophysical and social conditions in that county.

In recent years, very high spatial resolution satellite images have also been tested. Avelar et al. (2009) explored the relationship between land cover in Lima, Peru, and the distribution of socio-economic classes using a very high spatial resolution Quickbird image, census data and field data on socio-economic classes. Image data were classified using conventional supervised classification techniques to identify land-cover features such as green areas, water bodies, paved streets, bare soils, high-quality buildings and low-quality buildings. They used a regular square grid with a cell size of 1 km to store the percentages of each land-cover feature within each cell. Then, the combination of urban features was analyzed to obtain a socio-economic class for each cell based on membership rules for five socio-economic classes. The proposed method allowed the rapid assessment of socio-economic classes in large cities like Lima; however, the accuracy assessment showed that the method must be improved further to become fully operational and that a cell size of 1 km is too coarse for urban analysis. Improving on this work, Tapiador, Avelar, Tavares-Corrêa, and Zah (2011) developed a different approach to deriving the socio-economic class from very high-resolution satellite imagery in the same city. This approach is based on the assumption that there is a relationship between the socio-economic classes and the urban morphology, described in terms of the availability of green areas, sport facilities, private swimming pools and pavement in various conditions. A standard image classification process was applied to plot the components of the urban morphology, and a neural network classification process was used to assign social classes to each pixel in the image. The results were not as good as expected, but the researchers stated that the method could be used to identify deficiencies in urban services, to monitor social policies and as complementary information for decision making in urban planning. They also tested the applicability of this approach in Rio de Janeiro, Brazil, and Cairo, Egypt, and found that the method could be applied with few modifications.

Night-time satellite imagery on a regional scale from the Defense Meteorological Satellite Program (DMSP) has been used to estimate economic activity and poverty and to map urbanization dynamics at a global scale (Doll, 2008; Doll, Muller, & Elvidge, 2000; Elvidge et al., 2001; Elvidge, Sutton, Ghosh, & Tuttle, 2009; Zhang & Seto, 2011). Recently, high-resolution night-time imagery has been tested in Israel as an indicator of the demographic and socio-economic properties of urban areas at a local scale (Levin & Duke, 2012). Table 2 summarizes reported relationships among proxy variables of vegetation derived from satellite remote sensing and socio-economic variables measured in census and field surveys for several cities in the US. Table 3 presents similar information for surface temperature rather than vegetation.

The results of the aforementioned studies indicate that relationships among land-cover and socio-economic variables can be established in different cities around the world using satellite remote sensing, but local research is always needed, as the particular conditions of each city must be addressed and contrasted with socio-economic data to find useful correlations (Besussi, Chin, Batty, & Longley, 2010, chap. 2). The most obvious advantage of establishing these relationships in a city is that they allow social variables to be estimated quicker and at a lower cost than *in situ* measurements and for dates other than those of field surveys and census data, which in most countries are collected every 10 or 12 years. According to Phinn et al. (2002), five recurrent research themes in applications of remotely sensed data to urban environments are (i) land-use/land-cover mapping; (ii) assessment of the usefulness of texture measures to aid in separating urban land-cover and land-use types; (iii) impervious surface mapping for input to energy and moisture flux models; (iv) land-use/land-cover change mapping; and (v) application of empirical models to estimate biophysical, demographic and socio-economic variables. The last theme is of special interest for regional scientists, urban planners and policy makers. A sample of the applications of satellite remote sensing to the specific field of regional science in urban settings is described next.

3.1. Slum detection (deprivation hot spots)

According to UN-Habitat, a slum household is a group of individuals living under the same roof in an urban area that lacks one or more of the following: durable housing of a permanent nature, sufficient living space (not more than three people sharing the same room), easy access to safe water in sufficient amounts at an affordable price, access to adequate sanitation in the form of a private or public toilet shared by a reasonable number of people, and security of tenure.[5] The presence of slums in a city is an indicator of deprivation and poverty, and it is estimated that approxi-

[5] http://www.unhabitat.org/documents/media_centre/sowcr2006/SOWCR%205.pdf accessed 31 August 2011.

Table 3
Reported relationships among surface temperature and socio-economic variables, (+) positive correlation, (−) negative correlation.

Reported in	Lo (1997) and Lo and Faber (1997)	Jenerette et al. (2007)	Li and Weng (2007)
City	Athens-Clake, Georgia	Phoenix, Arizona	Marion County, Indiana
Image	Landsat TM	Landsat ETM+	Landsat ETM+
Method	Principal Component Analysis	Path Analysis	Factor Analysis Regression Analysis
Socio-economic variable			
Population density	+	+	+
Median income/per capita income/median household income	−	−	−
Percent minority/percent Hispanic		+	
Educational attainment	−		−
Number of rooms			−
Home year/year built		−	
Home value/ Median home value	−		−
Percent of urban use	+		
Percent of families under poverty level			+
Unemployment rate			+

mately one-third of the urban population in the developing world lives in slums (United Nations, 2011); hence, researchers are interested in the proper identification and characterization of slum neighborhoods.

The usefulness of satellite remote sensing for distinguishing a slum from its surrounding neighborhoods has been addressed in the last decade (Barros, 2008; Hofmann, Strobl, Blaschke, & Kux, 2008, chap. 6.1; Kohli, Sliuzas, Kerle, & Stein, 2012; Rhinane, 2011; Stow et al., 2007; Weeks, Hill, Stow, Getis, & Fugate, 2007). The degree of slumness of neighborhoods and places within a city has been estimated using remotely sensed data from very high spatial resolution platforms such as Quickbird, Ikonos and SPOT 5. Some approaches have used complementary socio-economic data on housing size and value, whereas others have used only texture and fractal dimensions derived from satellite imagery to develop statistical regressions. A very high resolution Quickbird satellite image with a pixel size of 0.6 m has been tested with three different strategies in the city of Accra, Ghana (Weeks et al., 2007). The first strategy was based on the Vegetation-Impervious surface-Soil (VIS) model of the urban scene devised by Ridd (1995)[6] and the use of image texture measures to infer land use from land cover data derived from satellite imagery (Weeks et al., 2007). A slum index map of the city was generated from census data to assess the usefulness of the remotely sensed data to perform the task. In this approach, it was found that the variability of a neighborhood's slum index can be predicted from remotely sensed data and that the amount of vegetation is the most important predictor, along with the image texture measures. By using these measures derived from remotely sensed images, it was possible to identify the parts of the city of Accra where 6 of the 10 worst slums are located. Stow et al. (2007) continued the work of Weeks et al. (2007) by using a more sophisticated classification scheme with the same satellite image in the same city. The image data were classified into non-residential, low socio-economic residential and high socio-economic residential areas using two different object-oriented image classification strategies, and their results were compared against the slum index map generated from census data. One strategy was based on spatial frequency characteristics of multispectral data for pixels within neighborhood-size segments, and the other was based on the proportions of vegetation, impervious surfaces and soil sub-objects (as in the VIS model) within similar segments. Both strategies showed similar accuracy, although the spatial patterns of land-use types were different, and a closer agreement with the map generated from census data was observed for the VIS land-cover sub-objects strategy.

Very high spatial resolution Quickbird images have also been tested for slum detection with object-oriented classification schemes in Sao Paulo and Rio de Janeiro, Brazil, with encouraging results (Hofmann et al., 2008, chap. 6.1; Kux, Novack, Ferreira, & Oliveira, 2010; Novack & Kux, 2010). Barros (2008) tested both Quickbird and Ikonos images of Recife and Campinas, Brazil, with an approach based on lacunarity texture analysis.[7] The slum locations were identified first by calculating an inhabitability index from census data, and image samples for those sites were then tested. The method proved to be useful for distinguishing images from slum and non-slum areas, and a strong correlation between lacunarity and inhabitability was found for both tested image types. It was also reported that this approach does not require intense field surveys, that it can be replicated and that it allows comparative analysis of multiple locations. Taubenböck, Wurm, et al. (2009) used an Ikonos image with an automatic object-oriented methodology and a semantic classification to classify the urban area of Padang, Indonesia, into suburbs, slums, low-class, middle-class and high-class areas. SPOT 5 images with 2.5-m spatial resolution have also proven useful to identify and quantify slums in Casablanca, Morocco, again using an object-oriented classification approach in an attempt to facilitate the monitoring and mapping tasks of Cities without Slums, a Moroccan government program launched in 2005 (Rhinane, 2011). Lacunarity texture measures have also been used successfully to identify urban slums in Hyderabad, India, using a Quickbird image (Kit, Lüdeke, & Reckien, 2012).

Very high spatial resolution satellite images have been tested successfully in several cities around the world, and it can be inferred that the situation will be similar for other cities in similar geographical contexts. The UN-Habitat objective definition of a slum is intended to be valid worldwide, and there is evidence of the usefulness of satellite remote sensing in cities with very different environmental conditions. However, there is still a research gap in slum detection from remote sensing that must be filled to develop a method applicable worldwide that takes advantage of the similar appearances of slums all over the world, such as crowding, small dwelling size and precarious and irregular street network patterns. Image texture measures, mathematical morphology and fractal dimensions such as lacunarity that use generalized urban morphology instead of local features are believed to

[6] Ridd (1995) proposed a model for urban ecosystem analysis that is very well suited to medium spatial resolution images and addresses the problem of mixed pixels. This model decomposes the urban scene into image fractions of vegetation, impervious surfaces and soil (V-I-S), and then urban land cover is classified according to the fractions for each pixel in a similar way as the tertiary sand-silt–clay diagram is used to quantify soil texture composition in the Earth sciences. This model is usually implemented through Spectral Mixture Analysis techniques (Lu & Weng, 2004; Rashed et al., 2005; Setiawan, Mathieu, & Thompson-Fawcett, 2006).

[7] Lacunarity is a fractal dimension that accounts for the distribution of empty spaces (lacunas) in an image (Barros, 2008).

be useful for this purpose. The work of Kohli et al. (2012) attempts to fill this gap by developing an ontological framework to conceptualize slums and to contribute to their detection and classification using very high resolution imagery, though this approach still requires adaptation to local conditions.

3.2. Quality of life index assessment

An important topic for urban policy makers is the objective measurement of the quality of life in urban areas through an index that takes into account not only socio-economic information about people but also information on the geographical context and environmental conditions of urban areas. An evaluation of the quality of life of the urban population is important to support decision making and sustainable urban management and planning and to measure policy outcomes (Craglia, Leontidou, Nuvolati, & Schweikart, 2004, Stathopoulou and Cartalis, 2006).[8] This approach is intended to assess several dimensions of quality of life: the social and the economic dimensions are measured from census data, and the environmental quality of the places inhabited is measured from remotely sensed data (Forster, 1983; Jensen, Gatrell, Boulton, & Harper, 2004; Lo, 1997; Lo & Faber, 1997; Weber & Hirsch, 1992). Various indices of quality of life, residential quality, attractiveness and a housing index have been estimated using remotely sensed data from Landsat MSS, TM, ETM+, and SPOT sensors and complementary data from censuses and surveys on housing size and value, population density, income and education. A description of different strategies to calculate a quality of life index with remote sensing data follows.

Forster (1983) shows how to derive a general residential quality index from satellite remote sensing data for Sydney, Australia. A correlation between average housing value and Landsat-derived reflectance data was demonstrated first. As in traditional hedonic models for house pricing, it was assumed that housing size is a surrogate of housing value and that a measure of housing quality and social environment may be positively related to a residential quality index. Vegetation content was assumed to be positively related as well, and other surfaces, such as roads and non-residential buildings, were assumed to have a negative impact on residential quality due to high noise and pollutant levels expected for those urban functions. Equations for residential quality index estimations from Landsat MSS reflectance data were developed using multiple regression analysis, which yielded a multiple correlation coefficient of 0.87. Although a residential quality map was not published, the analysis indicated that the major influence on residential quality came from vegetation content estimation from the infrared/visible bands ratio of the satellite image. Following similar principles, Weber and Hirsch (1992) calculated a quality of life index for Strasburg, France, using census data and the quality of the urban landscape as characterized and mapped from SPOT satellite images. Three different indices were developed and mapped from mixed data: a housing index, an attractiveness index and a quality index. The results produced realistic spatial distributions but were only weakly related to the census data that were usually used to define the urban landscape quality alone; these results thus demonstrate the importance of including environmental factors in the quantification of quality of life indices.

Lo (1997) and Lo and Faber (1997) used Landsat TM images combined with census data to assess the quality of life in Athens-Clarke County, Georgia, using image processing techniques and information overlay in GIS. The environmental variables extracted from the image data were land-use/land-cover as a percentage of urban use, vegetation as a normalized difference vegetation index (NDVI), and apparent surface temperature. The socio-economic variables extracted from the census data included population density, per capita income, median home value and percentage of college graduates. Two approaches were used to integrate the layers of data: principal components analysis (PCA) and GIS overlay. PCA showed a strong relation between biophysical data and socio-economic data, with NDVI showing strong negative correlations with land surface temperature and percentage of urban cover and positive correlations with per capita income, median home value and education. The first component was assumed to be an index of quality of life because it explained 54% of the variance and included both socio-economic and environmental variables. It was aggregated to the census block group level to produce a map of quality of life showing intra-urban variations. In the GIS overlay approach, all variables were ranked in terms of desirability for quality of life and combined at the census block group level to obtain a quality of life score map of the county. Both approaches produced very similar results, and both methods have the advantage that they can be easily performed with commercial remote sensing and GIS software.

Stathopoulou and Cartalis (2006) used a similar approach to assess quality of life in Athens, Greece, as did Li and Weng (2006, chap. 15) and Li and Weng (2007) for Indianapolis, Indiana. Stathopoulou and Cartalis (2006) identified not only the areas of the city with lower quality of life but also the variables that caused quality of life to be lowered in each area. Li and Weng (2006, chap. 15) developed a methodology to model quality of life in Marion County, Indiana, and validated it by applying it to Monroe and Vigo Counties in Indiana. It was concluded that the model may be useful for predicting quality of life and analyzing spatial variations within a specific region. Li and Weng (2007) also reported strong positive correlations of green vegetation with income, house value and education and negative correlations with temperature, impervious surface and population density for Indianapolis. Nichol and Wong (2006, chap. 12) used the same approach as Lo (1997) and Lo and Faber (1997) to assess urban environmental quality in the Kowloon Peninsula, Hong Kong. Field measurements were integrated with environmental parameters derived from Landsat ETM+ and Ikonos images. Although no accuracy assessment was made, they reported strong correlations between the results obtained from PCA and GIS overlay methods.

Interest in quality of life studies has recently increased. Hundreds of communities all over the world have conducted quality of life indicator research, and there are still important differences of opinion on the indicators of and contributors to quality of life and on how to use the information that indicators provide (Li & Weng, 2006, chap. 15, 2007). Moreover, each city has its own mix of environment and population attributes, which means that something that is found to be true for one city might be false for another. As with the relationships between land-cover and socio-economic variables, local research and knowledge must be considered for the results to be useful in policy making, urban planning and management.

3.3. Housing value estimation

Housing value estimation with satellite remote sensing has been tested in several cities around the world. House prices have been estimated using data from Landsat MSS, TM, ETM+ and ASTER sensors as well as complementary data from censuses and surveys of house structural attributes, population density, income, and distance to a central business district. Forster (1983) reported that the most significant variable for predicting average house value in the city of Sydney, Australia, was the number of rooms. House size was also believed to be a good predictor, and regression models for

[8] For more information on quality of life concepts and definitions, see Van Kamp, Leidelmeijer, Marsman, and de Hollander (2003) and Pacione (2003).

house value estimation from house size derived from a Landsat MSS image were developed. The results of these models were equivalent to the results obtained using known housing characteristics from census data. In a second step, Forster (1983) tested reflectance values and distance to a central business district directly in a regression equation with average house value. The results indicated that the average house value in Sydney can be predicted from Landsat-derived reflectance and that these results could be applicable in other cities with similar climate, residential density, population, size and urban morphology.

Several studies in US cities have found positive relationships between vegetation measures from remote sensing data and housing value, among other variables, using a variety of methods and approaches (Jensen et al., 2004; Li & Weng, 2007; Lo, 1997; Lo & Faber, 1997; Mennis, 2006). Jensen et al. (2004) used remote sensing and GIS to examine the relationships between a biophysical variable and standard socio-economic variables. They quantified the urban forest by measuring the Leaf Area Index (LAI, m^2 of leaves per m^2 of ground) of the vegetation in Terre Haute, Indiana, in 143 random sampling locations, which were later extended to the entire area of study using data from an ASTER satellite image and an artificial neural network. The result was integrated with census data using ordinary least squares regression techniques to establish relationships between urban LAI and population density, median income and median housing value. Urban LAI was positively related to the observed median home value and median income; the researchers stated that this relationship could be used to focus urban planning and management to ensure future investments are made where they are most needed. They went further in their conclusion to state that urban amenity variables could be used to explain and investigate the uneven distribution of urban resources.

Yu and Wu (2006) used a Landsat ETM+ image for house value modeling in Milwaukee, Wisconsin. They integrated environmental characteristics derived from the remotely sensed image with house structural attributes to model house values using two different techniques: global ordinary least squares regression and a regression tree approach. The environmental characteristics derived from the image were the fractions of vegetation, impervious surface and soil, which were measured through the normalized spectral mixture analysis developed by Wu (2004). The results showed that environmental characteristics have a strong influence on house values and that the performance of models is improved significantly when environmental characteristics are taken into account. The regression tree approach performed better than ordinary least squares regression, but both techniques yielded correlation coefficients above 0.9 between the predicted and observed house values.

All of the aforementioned studies have used coarse (Landsat MSS) and medium (Landsat TM and ETM+) spatial resolution imagery. The use of very high spatial resolution imagery in house value models deserves further research because it might provide better information for understanding urban housing markets (Yu & Wu, 2006). House size and house density are believed to be good predictors of house value, and these variables could be derived from very high spatial resolution imagery in addition to other environmental factors that could be integrated into house value models. Semantic and object-oriented image classification techniques are believed to be the most promising way to derive such information. This approach also offers potential for identifying housing submarket partitions on the basis of the differentiation of homogeneous urban morphology zones within a city. Taubenböck, Wurm, et al. (2009) tested the mentioned approach with an Ikonos image for classifying the urban area of Padang, Indonesia, into suburbs, slums, low-class, middle-class and high-class areas. They investigated the correlation of these classes with mean income and mean value of property, derived from a field survey, and found that the correlation is as expected but that location also played an important role in the value of property parameter, with the highest values located in the central area of the city. As with many other remote sensing applications, further research is needed to determine whether this correlation is valid in other urban environments around the world.

3.4. Urban growth

Remote sensing can play an important role in policy assessment related to urban growth, population dynamics and environmental issues within cities (Bhatta, Saraswati, & Bandyopadhyay, 2010a; Miller & Small, 2003). Quality of life, as described in Section 3.2, is one of several topics that have been addressed to improve urban policy making by monitoring the effects and consequences of policies on the ground (Pacione, 2003). Knowledge of actual urban growth trends is another topic of great importance to city planners, environment managers, and policy makers. There are considerable differences between the growth that is planned by a city government and the actual growth trends that take place on the ground in many cities in the developing world; therefore, monitoring and understanding those trends is important for understanding how to take proper action on them. Satellite remote sensing offers a reliable source of information about urban growth and sprawl processes because of its temporal and spatial characteristics (Doll, 2008; Rashed et al., 2005).

Very high-resolution imagery has been tested as a way to assess inner-city growth by detecting new buildings within neighborhoods using object-based approaches (Doxani, Karantzalos, & Strati, 2012; Tsai, Stow, & Weeks, 2011). Zhu, Woodcock, Rogan, and Kellndorfer (2012) found that the classification accuracies of urban and peri-urban land improve when SAR data are integrated with optical satellite imagery. Leinenkugel, Esch, and Kuenzer (2011) integrated SAR data with Quickbird and SPOT-5 imagery for impervious surface estimation and settlement detection and proposed a methodology for continuous monitoring of impervious cover in Can Tho Province, Vietnam. SAR and Landsat data have also been integrated to analyze the urbanization process in 27 mega-cities worldwide using object-oriented and pixel-based classification approaches and post-classification change detection to derive urban footprint products with accuracies over 80% (Taubenböck et al., 2012). Urban growth trends can be detected easily using medium spatial resolution satellite images, such as SPOT and Landsat TM, taking advantage of the very different spectral properties of urban manmade structures versus rural spaces. Land use patterns derived from remote sensing data provide additional means to describe urban growth types of peri-urban areas (Shi, Sun, Zhu, Li, & Mei, 2012; Sun, Wu, Lv, Yao, & Wei, 2012) and urban sprawl (Besussi et al., 2010, chap. 2; Soundranayagam, Sivasubramanian, Chandrasekar, & Durairaj, 2011). Night-time satellite imagery from the Defense Meteorological Satellite Programs Operational Linescan System (DMSP OLS) has also been used to assess urban sprawl in cities in the US (Sutton, 2003; Sutton, Cova, & Elvidge, 2006) and Australia (Sutton, Goetz, Fildes, Forster, & Ghosh, 2010). It is also remarkable that the whole Landsat archive is now freely available through the websites of the US Geological Survey and the Global Land Cover Facility at the University of Maryland, allowing researchers to perform urban growth studies for most cities worldwide from 1984 to the present using Landsat TM/ETM+ images.

Remotely sensed data and spatial modeling techniques have been applied to regional planning issues and specifically to estimations of future urban growth (Phinn et al., 2002; Ward, Phinn, & Murray, 2000). The need to estimate urban growth not only in terms of population growth, but also in terms of where most people are likely to be located, can be met using remote sensing data.

Ward et al. (2000) and Phinn et al. (2002) developed a framework for urban growth modeling that was tested in Queensland, Australia. Information about the urban extent and urban land-cover was obtained from Landsat TM images from two different dates using a hierarchical classification approach; this information was used as inputs to a cellular automata (CA) model that simulated local decision-making processes within an optimization framework that takes into account issues of sustainable urban development. One remarkable advantage of this approach is that it can be applied globally because it is supported on medium spatial resolution images that are now freely available.

Madhavan, Kubo, Kurisaki, and Sivakumar (2001) also used Landsat TM images to measure and analyze the spatial growth of the Bangkok metropolitan area of Thailand. Their approach was based on an image classification scheme and the VIS model (Gluch & Ridd, 2010, chap. 6; Ridd, 1995). Urban land-use/land-cover maps for 1988 and 1994 were produced from the classification processes, and changes in each of the urban land classes were measured with traditional post-classification methods. The VIS model was used in a later stage to visualize the trends of those changes in terms of the changes in vegetation, impervious surface and soil fractions and their trajectories for selected sites between the two dates. An analysis of these outputs led the researchers to conclude that the observed change in land-use led to improper urban land development in some areas of the city. Weng and Lu (2006, chap. 4) applied the same concept to characterize urban landscape patterns and to quantify spatial and temporal changes in urban landscape compositions in Indianapolis, Indiana.

Major determinants of urban growth in Wuhan city, PR China, from 1993 to 2000 were modeled using exploratory data analysis and spatial logistic regression techniques with remotely sensed data from a 2000 SPOT image and GIS layers including planning schemes, a 1993 land-cover map and population and statistics from census data (Cheng & Masser, 2003). This study showed that the major determinants of urban growth were urban road infrastructure and developed area and that master planning did not play a role in that specific period. On a broader spatial scale, Schneider, Seto, and Webster (2005) evaluated the urban growth in the Chinese Western provinces in response to the Go West policy that started in the 1990s. They used Landsat imagery (MSS, TM and ETM+) to map the land cover changes in Chengdu, Sichuan province and to investigate the spatial distribution of the development zones from 1978 to 2002. Major spatial trends were identified, including spatial clustering, specialization of land uses and periurban development. They were related to a growing private sector and uncoordinated large-scale investment by public agencies. A major reexamination of planning and policy was proposed to improve resource use and management, provide urban services where needed, reduce environmental degradation and promote urban sustainability.

Time series of Landsat imagery have been used to map and analyze urban expansion (Tian, Jiang, Yang, & Zhang, 2011; Wu & Zhang, 2012) and to analyze the spatio-temporal dynamics of green spaces within a city (Zhou & Wang, 2011). Michishita, Jiang, and Xu (2012) examined two decades of urbanization in four cities located in the Poyang Lake area, PR China, using a longitudinal dataset of Landsat imagery to derive a time series of urban land-cover fractions through Multiple Endmember Spectral Mixture Analysis (MESMA) and compared the fractions with socio-economic statistics. They found that the four cities were urbanized through different mechanisms and obtained positive correlations between built-up fractions and urban population, gross GDP and GDPs in secondary and tertiary industries.

Bhatta, Saraswati, and Bandyopadhyay (2010b) highlighted the differences in definitions and approaches used to measure urban sprawl among the research community. They mentioned that the general consensus is that urban sprawl is characterized by an unplanned and uneven pattern of growth that leads to inefficient resource utilization.[9] The spatial and temporal characteristics of urban sprawl have been monitored and modeled with medium-resolution images from Landsat MSS, TM, ETM+ and IRS LISS-III for the city of Ajmer, India, from 1977 to 2002 (Jat, Garg, & Khare, 2008). Urban sprawl was derived from classified satellite images and was analyzed using landscape metrics and multivariate statistical techniques to establish relationships with its causative factors. Their results showed that land development increased almost three times as much as the population did. The obtained relationships between the present trends of urban sprawl and their causative factors can be used by local authorities for land policy reexamination and improvement.

Sutton (2003) and Sutton et al. (2006) used night-time satellite imagery from DMSP OLS to characterize urban sprawl in the US using night-time lighting as a proxy of urban extent. Sutton (2003) measured urban sprawl adjusted to the total population of an urban area and derived aggregate measures of per capita land consumption that allowed comparisons between different metropolitan areas across the US. He found that western cities such as Los Angeles and San Francisco have lower levels of urban sprawl than do inland cities such as Atlanta, St. Louis and Minneapolis. Sutton et al. (2006) characterized the exurban areas in the US, defined as the expansive areas of low light surrounding all major metropolitan areas, and proposed a classification scheme of land cover into urban, exurban and rural areas based on DMSP OLS data. Well-lit areas were characterized as urban, low-lit areas as exurban and dark areas as rural. They stated that this scheme is better than an urban, suburban and rural classification scheme based on census data for characterizing the population and land use of industrialized countries because the distinction between urban and exurban is more pronounced than the distinction between urban and suburban. Sutton et al. (2010) used the same approach to quantify urban sprawl in several cities in Australia and to contrast the results with those of their previous investigation in the US. They found that cities with an equivalent population in the US occupy larger areal extents than Australian cities, which suggests that sprawl is lower in Australian cities than in American cities.

There are many approaches and measures to evaluate urban growth and sprawl (Belal & Moghanm, 2011; Bhatta et al., 2010a, 2010b; Jat et al., 2008; Lu, Moran, & Hetrick, 2011; Sudhira, Ramachandra, & Jagadish, 2004; Tole, 2008), and satellite remote sensing has proven to be a useful tool to derive ground information to evaluate planning and policy outcomes on a large scale. The studies reviewed so far show the usefulness of medium spatial resolution satellite imagery for urban growth and land development assessment.

3.5. Population estimation

An understanding of the population size and spatial distribution in urban areas is essential for social, economic and environmental applications (Li & Weng, 2005; Liu, Kyriakidis, & Goodchild, 2008). The use of remote sensing for population estimation started in the mid-1950s as a way to address the shortcomings of the decennial census, such as its high cost, low frequency and intense labor requirements (Liu & Herold, 2006, chap. 13). Regional-scale population estimates can be achieved through the quantification of urbanized built-up area from remote sensing data using statistical relationships with the total settlement population. In urban areas, population estimation by remote sensing often involve counting

[9] For more information on remote sensing-derived measures of urban sprawl, see Bhatta et al. (2010b).

dwelling units, measuring land areas, and classifying land use. The last requirement results from the close correlation of land use with population density in urban areas. Ground data on the average number of persons per dwelling unit and for different land uses are always needed to calibrate models (Jensen & Cowen, 1999). The general strategy to achieve population estimations from remote sensing data is to establish statistical relationships between census or field survey data and remotely sensed data using regression analysis techniques (Harvey, 2002; Liu et al., 2006; Lo, 1995; Pozzi & Small, 2005; Yuan, Smith, & Limp, 1997). Data from SPOT, Landsat TM and ETM+ sensors have been used along with census or survey data on population counts to estimate population size. Recently, building heights derived from LiDAR (Light Detection and Ranging) data and very high resolution imagery have also been used to estimate population counts at an intra-urban scale.

Lo (1995) developed methods to extract population and dwelling unit data from a SPOT image of the Kowloon metropolitan area in Hong Kong. Different regression models were applied to link the spectral radiance values of image pixels with population densities. Accurate estimates of population and dwelling units were obtained at the macro level for the whole study area, but intra-urban variations and micro-level estimates tended to be of low accuracy because of the difficulty of discriminating residential from non-residential use in multifunctional buildings in the satellite image. In a regional-scale study, Yuan et al. (1997) found high correlations between land cover classified from a Landsat TM image and population counts from census data. By applying regression and scaling techniques, they were able to obtain a population distribution map with much more detail than census data alone offered for four counties in central Arkansas.

Harvey (2002) used a Landsat TM image and census data for Ballarat and Geelong, Australia, to allocate population estimates to each pixel of the image and overcome the problem of spatial aggregation of census data. The satellite image was first classified into residential and non-residential classes, and initial reference populations were distributed uniformly for each census zone across its residential pixels only. Then, pixel populations were related to pixel spectral values and re-estimated pixel populations using an expectation–maximization regression algorithm, and the regression equation was tested in a second image. The relative error of global estimations was less than 1% in both images, but it rose to approximately 16% and 21% in the individual census zones. Wu and Murray (2005) followed a similar approach with a Landsat ETM+ image, but instead of using pixel spectral values, they used the fraction of impervious surfaces in residential areas. Li and Weng (2005) integrated a Landsat ETM+ image and census data for estimating intra-urban variations in population density in Indianapolis, Indiana, using several remote sensing-derived variables as predictive indicators, correlation analysis to explore their relationships with population data, and step-wise regression analysis to develop models. Liu et al. (2006) stated that these results were valuable for improving population estimations, but the spatial resolution of 30 m limits their utility in urban applications. Liu and Herold (2006, chap. 13) highlighted the use of high spatial resolution satellite imagery to study intra-urban population characteristics.

Although very high spatial resolution imagery has been available for at least 10 years, since the launch of the Ikonos and Quickbird satellite programs, little research has explored the use of this type of imagery for population estimation purposes (Liu et al., 2008). Liu et al. (2006) and Galeon (2008) are two examples of this type of research. Liu et al. (2006) explored the correlation between census population density and image texture with a very high spatial resolution Ikonos image of Santa Barbara, California, using linear regression. The spatial unit used in this analysis was the census block with homogeneous land use. Different methods for describing image texture were tested, and the correlation was found to vary depending on the method used. The obtained correlation between image texture and population was not strong enough to predict or forecast residential population size, but the researchers concluded that image texture could be used to refine census-reported population distributions using remote sensing and to support smart interpolation programs to estimate human population distributions in areas where detailed information is not available. Galeon (2008) used a Quickbird satellite image to estimate the population size in informal settlements using a field survey and regression analysis for the University of Philippines campus area. The researchers obtained accurate estimates of population size with first-order equations for the slum areas but not for the semi-formal housing areas present on the campus.

Although LiDAR techniques have been available since the 1960s, they have only become commonly used in the past few years (Lwin & Murayama, 2009). LiDAR data can now provide very accurate height information for land surface features such as buildings and trees. Digital volume models (DVMs) derived from LiDAR data are increasingly being used for population estimation at the urban scale and are being integrated with very high resolution imagery with good results (Qiu, Sridharan, & Chun, 2010; Lwin & Murayama, 2009, 2011, chap. 6; Ramesh, 2009; Weng, 2012). SPOT and Landsat TM imagery has been popular among population estimation applications of satellite remote sensing because of its relative success in regional- and medium-scale studies. At the urban or intra-urban scales, further research is needed to establish the best methods and procedures for population estimation, taking advantage of the very high spatial resolution satellite imagery and LiDAR data that are now widely available. Ground truth, in the form of field surveys and census data, is always needed, but the goal is to achieve the highest possible accuracy while minimizing fieldwork to keep the research both cost effective and operationally practical.

3.6. Social vulnerability assessment

The concepts of hazard, disaster, risk and vulnerability are often used interchangeably and have different implications in different scientific disciplines (Rashed, 2005, chap. 17; Rashed, Weeks, Couclelis, & Herold, 2007, chap. 9). However, in the broad and multidisciplinary field of risk management, researchers agree on the definitions of the concepts of hazard, vulnerability and risk. Hazard is related to the occurrence of a physical phenomenon or event that constitutes a threat to society, whereas vulnerability is related to the ability of the society to cope with the impact of the hazard, and risk is understood as the combination or product of the probability of a hazards occurrence and the degree of vulnerability of the society or community exposed to the hazard (Rashed, 2005, chap. 17; Taubenböck et al., 2008). The coping ability of the society involves several factors and relationships of a physical, economic, social and political nature. Social vulnerability refers to the social aspects of a community that are related to the conditions in which it can face a hazard (Botero, 2009). Although it has been stated that remote sensing can provide a fast and cost-effective way to derive information about many of the factors that shape social vulnerability to natural hazards (Taubenböck et al., 2008), there are few published works on the assessment of social vulnerability to natural hazards in urban settings with remote sensing data.

Social vulnerability to different types of natural hazards has been estimated using remotely sensed data from the Landsat TM, Quickbird, and Ikonos platforms and complementary data from censuses and surveys. Taubenböck et al. (2008) listed the possible uses of remote sensing for measuring social status indicators of vulnerability to earthquakes and tested them using very high and medium spatial resolution satellite images of Istanbul, Turkey, from Ikonos and Landsat. An automatic object-oriented and

Table 4
Regional science applications in urban settings and remote sensing data.

Application	RS data	Complementary data	References
Slum detection	Ikonos Quickbird SPOT 5	Census Field survey	Weeks et al. (2007) Hofmann et al. (2008, chap. 6.1) Novack and Kux (2010) Kux et al. (2010) Barros (2008) Taubenböck, Wurm, et al. (2009) Rhinane (2011) Kit et al. (2012) Kohli et al. (2012)
Quality of Life index	Landsat MSS Landsat TM Landsat ETM+ SPOT 2 ASTER	Census	Forster (1983) Weber and Hirsch (1992) Lo (1997) Lo and Faber (1997) Jensen et al. (2004) Stathopoulou and Cartalis (2006) Li and Weng (2006, chap. 15) Nichol and Wong (2006, chap. 12) Li and Weng (2007)
House value estimation	Landsat MSS Landsat ETM+ ASTER Ikonos	Census Field survey	Forster (1983) Jensen et al. (2004) Yu and Wu (2006) Taubenböck, Wurm, et al. (2009)
Urban growth	Landsat TM Landsat ETM+ IRS-1C SPOT 4 SAR DSMP OLS	Census	Ward et al. (2000) Phinn et al. (2002) Madhavan et al. (2001) Cheng and Masser (2003) Schneider et al. (2005) Jat et al. (2008) Bhatta et al. (2010a) Sutton et al. (2010) Tsai et al. (2011) Zhu et al. (2012) Taubenböck et al. (2012) Leinenkugel et al. (2011)
Population estimation	Landsat TM Landsat ETM+ SPOT 3 Ikonos Quickbird LiDAR	Census Field survey	Lo (1995) Yuan et al. (2008) Harvey (2002) Wu and Murray (2005) Liu et al. (2006) Galeon (2008) Ramesh (2009) Lwin and Murayama (2009) Qiu et al. (2010) Lwin and Murayama (2011) Weng (2012)
Social vulnerability assessment	Ikonos Quickbird	Field survey	Taubenböck et al. (2008) Ebert et al. (2007, 2009) Rashed and Weeks (2003b) Rashed et al. (2007, chap. 9)

fuzzy-based approach was used to classify the Ikonos image into land-cover classes, and the researchers used this information to derive indicators related to the physical and demographic components of vulnerability. A time series of Landsat data was used to map and assess building ages and urbanization rates. Built-up density, accessibility, population density, building age, and urbanization rate indicators were derived from satellite imagery. Their results showed the capability of remote sensing to assess several aspects of social vulnerability and their spatial distributions, but the researchers stated that the main limitation of this approach lies in the lack of knowledge of how to derive reliable values for the socio-economic and political components of vulnerability.

Ebert, Kerle, and Stein (2007, 2009) tested whether it was possible to evaluate social vulnerability to floods and landslides in Tegucigalpa, Honduras, using remote sensing data. They used very high resolution images from Quickbird and ResourceSat P-6 satellites as well as elevation models and risk maps of floods and landslides to estimate proxy variables to describe the physical aspects of the urban environment. The proportions of vegetation and built area, road conditions, roof and building materials, the position of the building relative to the slope, the building height, the number of evacuation routes and the distance between the buildings and evacuation routes, among other variables, were derived from satellite images. Although remotely sensed data by themselves cannot replace traditional methods such as census and surveys, the synergy of the use of remote-sensed data with field surveys, the application of a census and the combination of these data in a GIS helped to improve the efficiency, frequency, and coverage of the evaluation of social vulnerability at different spatial scales. Object-oriented analysis techniques proved useful for deriving proxy variables that describe non-physical indicators of social vulnerability. The importance of using these techniques that combine traditional approaches with the analysis of remotely sensed data lies in the possibility of transference to other regions and the appli-

Table 5
Image processing methods and regional science applications of remote sensing data in urban settings.

Method	RS data	Application	References
Direct radiance measures and regression analysis	Landsat MSS SPOT 3	Quality of life House value estimation Population estimation	Forster (1983) Lo (1995)
Per-pixel classification	Landsat TM Landsat ETM+ SPOT 4	Land policy assessment Population estimation	Ward et al. (2000) Phinn et al. (2002) Cheng and Masser (2003) Schneider et al. (2005) Yuan et al. (2008) Harvey (2002)
Vegetation index (NDVI/SAVI)	Landsat TM Landsat ETM+ SPOT 2	Quality of life	Weber and Hirsch (1992) Lo (1997) Lo and Faber (1997) Jensen et al. (2004) Stathopoulou and Cartalis (2006) Nichol and Wong (2006, chap. 12) Li and Weng (2007)
Vegetation index (LAI) Object-oriented classification	ASTER Quickbird SPOT 5 Ikonos LiDAR SAR	House value estimation Slum detection Social vulnerability assessment Population estimation Urban growth	Jensen et al. (2004) Weeks et al. (2007) Hofmann et al. (2008, chap. 6.1) Novack and Kux (2010) Kux et al. (2010) Rhinane (2011) Taubenböck et al. (2008) Taubenböck, Wegmann, et al. (2009) Ebert et al. (2007) Ebert et al. (2009) Ramesh (2009) Tsai et al. (2011) Doxani et al. (2012) Zhu et al. (2012)
VIS model	Landsat ETM+ Landsat TM	House value estimation Land policy assessment Population estimation Urban growth	Yu and Wu (2006) Madhavan et al. (2001) Wu and Murray (2005) Gluch and Ridd (2010, chap. 6)
Landscape metrics	Landsat MSS Landsat TM Landsat ETM+ IRS-1C	Land policy assessment Urban growth and sprawl	Jat et al. (2008) Besussi et al. (2010, chap. 2) Soundranayagam et al. (2011) Shi et al. (2012) Sun et al. (2012)
Texture measures Lacunarity Spatial metrics Co-occurrence matrix Semi-variance	Ikonos Quickbird	Slum detection Population estimation Land policy assessment Social vulnerability assessment	Barros (2008) Kit et al. (2012) Liu et al. (2006) Rashed and Weeks (2003b) Rashed et al. (2007)

cability of these methods in a sustainable way over time (Ebert & Kerle, 2008).

Rashed (2005, chap. 17), Rashed et al. (2007, chap. 9) and Taubenböck et al. (2008) have analyzed the potential of remote sensing to derive useful information on the social and physical characteristics of urban settings that increase or decrease the capacity of a local community to cope with a natural hazard. Rashed (2005, chap. 17) emphasizes that many of the findings of urban change studies that have used remote sensing (such as those mentioned in Section 3.4) can help researchers to better understand the implications of these changes for urban vulnerability because urban changes are related to land-use practices, resource management and hazard mitigation policies in cities. Advances in using landscape metrics in urban morphology characterization for the city of Los Angeles, California, have been made to infer socio-economic indicators that could be related to social vulnerability to earthquakes (Rashed, Weeks, Roberts, Rogan, & Powell, 2003; Rashed et al., 2007, chap. 9). Research in different cities and environments is still needed to develop a robust framework in which remote sensing-derived measures can play a leading role in the assessment of social vulnerability to natural hazards.

4. Conclusions

This review describes major research themes of regional science and remote sensing in urban environments: relationships between land cover and socio-economic variables, slum and urban deprivation hot spots, urban quality of life, estimation of housing values, urban growth analysis, population estimation, and urban social vulnerability assessment. Human health applications of remote sensing tend to operate on a regional scale and are oriented toward the detection of environmental conditions that influence vector disease propagation and early warning systems (de Sherbinin et al., 2002; Johnson, 2007, chap. 6). To date, urban public health issues have been examined through satellite remote sensing by mapping urban vegetation and impervious surfaces and relating them to the urban heat island phenomenon and the health conditions of local residents (Dadvand et al., 2012; Harlan, Brazel, Prashad, Stefanov, & Larsen, 2006; Liu, Taylor, Wilson, Yamada, & Hoch, 2007; Lo & Quattrochi, 2003; Rhew, Vander Stoep, Kearney, Smith, & Dunbar, 2011; Weeks, Getis, Hill, Agyei-Mensah, & Rain, 2010). Tables 4 and 5 summarize the data and methods most commonly used in regional science applications of remote sensing data in urban settings. Linking socio-economic and demographic information from field surveys with satellite data from different sensors and relating empirical measurements, spatial theory, and modeling have been successful approaches (Herold, 2009, chap. 2).

Researchers have found consistent relationships between environmental factors derived from satellite remote sensing data and socio-economic variables in several cities in the US (Jenerette et al., 2007; Jensen et al., 2004; Li & Weng, 2007; Lo, 1997; Lo & Faber, 1997; Mennis, 2006). Object-oriented image classification, image texture measures and spatial metrics have been successfully applied to identify deprivation hot spots or slums in cities in developing countries (Barros, 2008; Hofmann et al., 2008; chap. 6.1; Kit et al., 2012; Kux et al., 2010; Novack & Kux, 2010; Rhinane, 2011; Stow et al., 2007; Taubenböck, Wurm, et al., 2009; Weeks et al., 2007). The assumption underlying these findings is supported by Tobler's first law of geography, Everything is related to everything else, but near things are more related that distant things (Tobler, 1970), and was explained by Taubenböck, Wurm, et al. (2009) as a self-segregation of social groups in urban environments according to their economic status, amongst other aspects. This assumption is also used in geodemographics, in which it is said that the consumer behavior of a person living in a certain neighborhood can be inferred from information about other people living in the same neighborhood, or even in the same type of neighborhood (Harris, Sleight, & Webber, 2005). However, these relationships always need to be investigated and tested in each city where they are to be applied because the phenomena are highly specific. As stated by de Sherbinin et al. (2002), findings for one city can be quite the opposite of those for another city, even in the same country; e.g., the amount of vegetation in Detroit, Michigan, is an indicator of urban decay, whereas vegetation is positively correlated with income, house value and educational attainment in Denver, Colorado, and Phoenix, Arizona, among other cities.

Urban growth dynamics and urban sprawl have been assessed using satellite remote sensing data. Even though the Landsat sensor's spatial resolution is coarser than the requirements stated by Jensen and Cowen (1999), its images have been used successfully in several studies using the VIS model approach (Ridd, 1995) and spectral mixture analysis techniques to assess longitudinal changes in land use-land cover and urban growth quantitatively (Ward et al., 2000; Madhavan et al., 2001; Phinn et al., 2002; Wu & Murray, 2005; Yang & Liu, 2005, Yuan, Wu, & Bauer, 2008). Policy makers and urban planners can use the results of this research to better understand the urban growth trends in their cities and to plan better for future growth.

Demographers and other regional scientists can also benefit from using satellite remote sensing data to estimate population counts in urban settlements where detailed information is not available (Liu et al., 2006). Economists could also benefit from integrating remote sensing data into urban housing market models to account for environmental factors that influence property values, and they can use urban morphology measures derived from remote sensing imagery to identify housing submarkets (Yu & Wu, 2006). Further research is needed to demonstrate the utility and transferability of this approach.

Satellite remote sensing provides a fast and reliable way to derive useful information for social vulnerability assessment (Taubenböck et al., 2008, Ebert et al., 2007, Ebert et al., 2009, Rashed & Weeks, 2003a, Rashed et al., 2007, chap. 9). Particularity is one of the most important concepts in the assessment of social vulnerability, and satellite remote sensing can provide data for place-based analysis (Rashed et al., 2007, chap. 9). Further research in cities with different environments is needed to develop a robust framework in which measures derived from remote sensing can play a leading role in the assessment of social vulnerability to natural hazards.

This review shows that, with the exception of urban growth analysis, little research has used remote sensing to analyze space–time dynamics. For example, the space–time variations in a quality of life index before and after a government investment in public spaces and other urban services could be used to assess whether government actions have produced the expected results. Policy makers and urban planners could benefit from similar analyses of other topics, such as housing markets, deprivation hot spots, and vulnerability to natural hazards in urban settings, to help them allocate resources where they are most needed. Satellite remote sensing data have been successfully used in all of the aforementioned research areas, but some regional scientists remain skeptical about using remote sensing to derive information for their work. Although many local and regional government agencies are now using remote sensing to map, monitor and model the composition and growth of cities, more local research is needed to show the real potential and utility of satellite remote sensing for regional science in urban environments.

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