A CIESIN Thematic Guide to Social Science Applications of Remote Sensing

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1.0 – Social Science Applications of Remote Sensing

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Abstract

Remote sensing has traditionally been the province of Earth scientists and the national security community. Early civilian satellite instruments were designed largely to meet the needs of weather forecasting, earth systems science and natural resource management. Social science applications were, generally speaking, not even considered. However, since the late 1980s, this began to change as a number of social scientists began to apply remote sensing imagery to understand the underlying social processes behind diverse phenomena such as deforestation, desertification, and urbanization. Since that time there has been a dramatic increase in the quantity and breadth of research that can be broadly categorized under the umbrella of "social science," with newer applications in the fields of archaeology, demography, and human health and epidemiology. Chapter 3 of this guide provides an introduction to remote sensing for non-technical audiences. Chapter 4 addresses fundamental issues in the application of remote sensing to social science research questions. Finally, Chapter 5 provides examples of social science applications in six different fields, and Chapter 6 provides a table listing the characteristics of major sensors.

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The richness of this guide resides in the many and varied links to bibliographic resources, many of which are available on-line. Readers are encouraged to toggle between the written sections and the references and related resources to gain a better sense of the breadth of research in this important area of study. Note that references are dynamically linked to sections of the guide. The Reference section in the table of contents provides references for the entire guide, but by toggling to references from a particular chapter or section, only references for that chapter or section will appear. The full bibliography of the Social Science Applications of Remote Sensing Guide exceeds 600 entries, many of which were not specifically cited in the text. To access the larger bibliography, users are encouraged to use the bibliographic search page. A full description of CIESIN Thematic Guide functionality can be found by accessing the help page from the navigation bar.

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2.0 – Introduction

Remote sensing has traditionally been the province of earth scientists and the national security community. Early civilian satellite instruments were designed largely to meet the needs of weather forecasting, earth systems science and natural resource management. While the results were often *socially useful* in a whole range of fields (agriculture, disaster mitigation, and forest management, to name a few), social science research questions were largely ignored. Some early remote sensing scientists pondered potential social science applications such as population counts, but the instruments themselves were never designed with this in mind, and few if any social scientists seriously considered how the data might be used in their research. However, since the late 1980s, this began to change as a number of social scientists began to apply remote sensing imagery to understand the underlying social processes behind diverse phenomena such as deforestation, desertification, and urbanization. Since that time there has been a dramatic increase in the quantity and breadth of research that can be broadly categorized under the umbrella of "social science," with applications in the fields of archaeology, demography, and human health and epidemiology. This increase is determined in part by a growing awareness of the potential of remote sensing to inform issues of relevance to the social sciences, and by the higher spatial and spectral resolution of new satellite sensors that make them increasingly applicable to social science research questions.

This guide has a number of objectives. Firstly, it seeks to provide an introduction to the use of remote sensing to social scientists. In Chapter 3, the guide provides an introduction to remote sensing technology and pointers to a number of on-line tutorials (through the references and related resources). Secondly, it highlights the advantages of remotely sensed data for social science research, and seeks to highlight some of the key methodological concerns when integrating remote sensing with socioeconomic data (Chapter 4). And thirdly, it summarizes the methodology and results of research using remote sensing in several different fields (Chapter 5). Finally, Chapter 6 provides a table listing the technical specifications of various remote sensing instruments together with descriptions of the kinds of things these sensors can detect.

The guide owes much to pioneering work in this field that was compiled by the National Research Council in 1998 under the title *People and Pixels: Linking Remote Sensing and Social Science* (Liverman *et al.* 1998). This was the first edited volume to systematically compile and evaluate state-of-the-art remote sensing applications in social science research. In addition to an overview piece, chapters in that volume addressed:

- land-use and land-cover change (LUCC) research
- linking satellite, survey and census data
- analysis of population dynamics based on LUCC
- archaeological research
- urban attributes modeling
- famine early warning systems
- health applications
- remote sensing data available to social scientists

We have sought to build on this foundation by focusing on progress towards the application of remote sensing data, and the integration of remote sensing data with socioeconomic data, in a number of related research areas:

- population and the environment
- human health and epidemiology
- archaeology and anthropology
- international relations, law and policy
- land use and land cover
- urban studies

These are covered in Chapter 5.

As noted above, while remote sensing has frequently been used for *socially useful purposes*, such as weather forecasting, disaster response or predictions of crop yields, there are relatively fewer examples of remote sensing applications within the context of *social scientific research* (Rindfuss and Stern 1998). Our focus here is the integration of remote sensing in social science research (the agenda of the academic social sciences) and social scientific research (social research using scientific methods). This could be research that seeks to understand the socioeconomic drivers (e.g., population size and location, policies, and market forces) of changes in the landscape or the environment detectable by remote sensing imagery. It could also be research that seeks to understand how biophysical factors, geographic location, and infrastructure (also detectable by remote sensing images) impact upon human activities, health and well being. Finally, it could be research that seeks to better understand the relationship of these factors in the past, as would be the case in archaeology and history. These research applications explicitly seek to test hypotheses about the relationship between humans and the environment in the past, the present, and, in some cases, into the future (through modeling). To a lesser extent, this guide also covers research conducted by government agencies and the private sector on social phenomena, which is driven by the need to solve social problems as well as by commercial interest.

3.0 - Remote Sensing[1]

This chapter provides an overview of remote sensing technology for non-specialists. Fundamentals of remote sensing and image interpretation are described in a number of online tutorials, including NASA's Remote Sensing Tutorial and the Canada Center for Remote Sensing Tutorial (see References and Related Resources for URLs). The International Society of Photogrammetric Engineering and Remote Sensing (ISPRS) also has lists of on-line remote sensing resources. For those desiring more detailed reference materials on remote sensing, it is recommended that they obtain Lillesand and Kiefer's *Remote Sensing Image Interpretation* or Jensen's *Remote Sensing of the Environment* (see References and Related Resources for full citations).

3.1 History of Remote Sensing

Modern remote sensing began with invention of the camera obscura in early 1800s. Shortly thereafter, the first aerial photograph was taken in Paris in 1858 with a camera mounted on a balloon. During World War I cameras, mounted on planes were used in military reconnaissance. The greatest expansion of the use of aerial photography occurred during World War II primarily for military reconnaissance. The military also pioneered the development of remote sensing outside the eye's visible range, such as near infrared imagery for discriminating camouflage from real vegetation. After the war several civilian applications were developed including hazard mapping, vegetation mapping and planning. Until the early 1960s, the aerial photograph remained the only tool for depicting the earth's surface from a vertical (or nadir) perspective.

Space remote sensing began with the launch of the first military intelligence satellite in 1958. In 1960 the first U.S. meteorological satellite, TIROS-1, was launched by an Atlas rocket into orbit. This satellite was devoted mainly to looking at clouds. Onboard this satellite, were the first non-photographic sensors. TIROS, for Television Infrared Observation Satellite, used vidicon cameras to scan wide areas at a time to produce generalized weather maps. The 1972 launch of the Earth Resource Technology Satellite (ERTS), later renamed Landsat, initiated the era of land remote sensing. These satellites were equipped with multi-spectral sensors dedicated to continuous imaging of the earth's surface.

3.2 Fundamentals of Remote Sensing

The process of remote sensing involves the detection and measurement of radiation of different wavelengths reflected or emitted from distant objects or materials, by which they may be identified and categorized by class/type, substance, and spatial distribution. The background required for use of remote sensing tools may seem overwhelming at first. The decisive factor in the successful application of remote sensing data, however, need not be the technical sophistication of the user, but rather the suitability and precise use of the tool to obtain accurate and relevant data. A general grasp of the technical process that transforms electromagnetic energy into useful information can improve and expand the appropriate use of these tools. Nevertheless, depending on the application, social scientists wishing to work with remote sensing imagery would do well to partner with physical scientists with a deeper understanding of how the imagery represents physical processes on the ground.

[1] This chapter was revised January 2006.

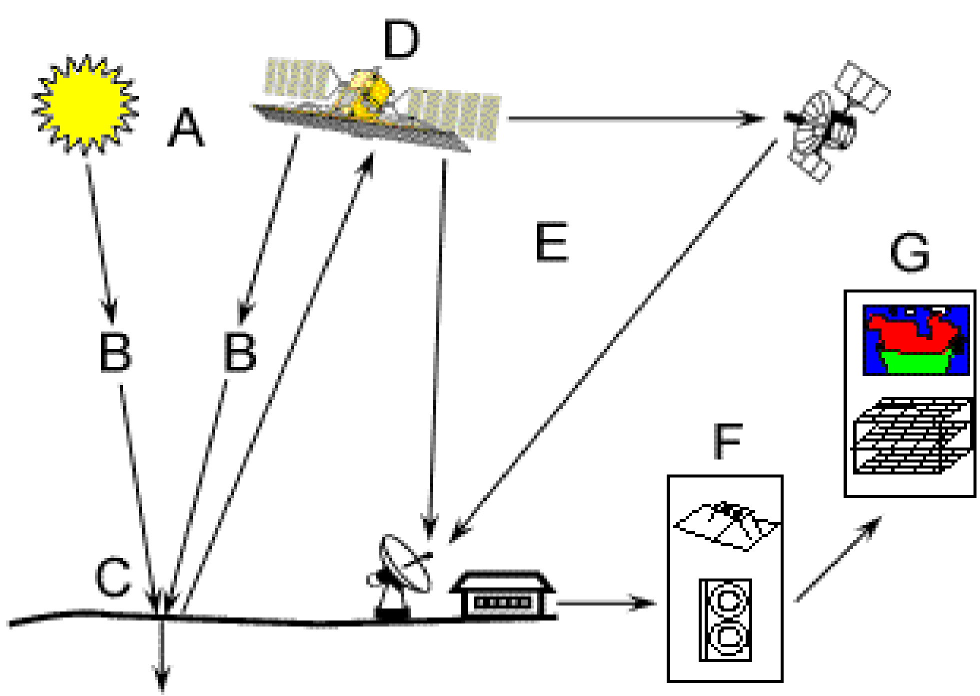
In the broadest sense, remote sensing refers to information gathered by measuring and interpreting signals. To use perhaps the simplest analogy, the human body is constantly involved in a variety of remote sensing tasks. Hearing and vision are two obvious examples, involving the gathering and interpretation of sound and light waves, both in limited ranges of the entire sound and light spectra.

Active and *passive* remote sensing are used to describe the way sensors gather data. To illustrate the two types of sensors, consider a snapshot camera, a sensor that captures electromagnetic radiation in the visible spectrum. Outdoors in full daylight, a camera is ordinarily used as a passive sensor in that it receives reflected visible light from its surroundings and uses optics, a shutter, and film to create a lasting image. At night, on the other hand, when there is inadequate light for most cameras to capture a useable image, the camera may employ a flash. The flash is emitted from the camera and bounces off the object to illuminate it, just as an active (or radar) sensor sends a burst of energy towards its target and then receives the reflected radiation.

A key factor in the choice between passive and active sensor is the relative strength of the potential signal each system must measure. For a passive system, the source of the signal is ultimately the sun, which emits electromagnetic radiation at its highest intensity between the ultraviolet and infrared ranges (see discussion of electromagnetic energy in Section 3.3). In the radar wavelength ranges, however, sensors must provide a signal of sufficient intensity to travel to the earth, and return with enough strength to be distinguishable from the background "noise" from other sources.

All remote sensing systems – active and passive – generally have the following seven elements (see Figure 1).

Figure 1. Diagram of Elements of a Remote Sensing System



Source: Canadian Centre for Remote Sensing, Fundamentals of Remote Sensing

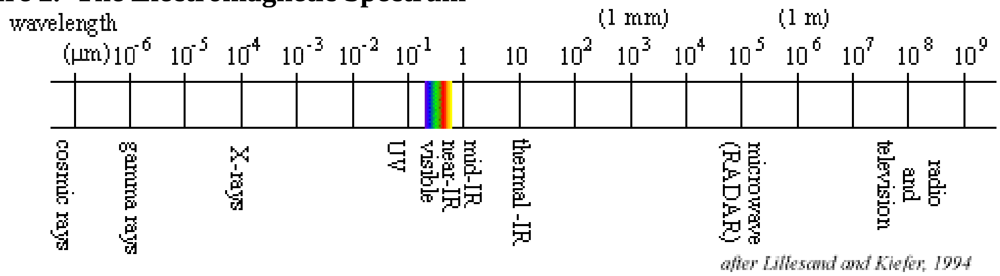
Energy Source or Illumination (A) – A basic requirement for remote sensing is an energy source to illuminate or provides electromagnetic energy to the target of interest. For passive instruments, this is usually the sun; for so-called active instruments, the sensor itself emits an pulse of energy.
Radiation and the Atmosphere (B) - As the energy travels from its source to the target, it will come in contact with and interact with the atmosphere it passes through. This interaction also takes place a second time as the energy travels from the target to the sensor. Inevitably there is a certain degree of atmospheric scattering of radiation (see Section 3.3).
Interaction with the Target (C) - Once the energy makes its way to the target through the atmosphere, it interacts with the target depending on the properties of both the target and the radiation.
Recording of Energy by the Sensor (D) - After the energy has been scattered by, or emitted from the target, a sensor (remote - not in contact with the target) collects and records the electromagnetic radiation.
Transmission, Reception, and Processing (E) - The energy recorded by the sensor has to be transmitted, often in electronic form, to a receiving and processing station where the data are processed into an image (hardcopy or digital).
Interpretation and Analysis (F) - The processed image is interpreted, visually or digitally/electronically, to extract information about the target illuminated.
Application (G) - The final element of the remote sensing process is achieved by applying the information that has been extracted from the imagery about the target in order to better understand it, reveal some new information, or assist in solving a particular problem.

3.3 Electromagnetic Energy

Remotely sensed data are collected in many regions of the electromagnetic spectrum (Figure 2). Data recorded from each part of the spectrum can provide distinct information on characteristics of the Earth's surface or properties of the atmosphere. For example, healthy green vegetation reflects highly in the near-infrared region of the spectrum, whereas water bodies tend to reflect only a small amount of incoming radiation in the visible region. All remote sensing instruments collect electromagnetic radiation that is reflected, emitted, or scattered from the Earth's surface and atmosphere. So-called active sensors such as radar and lidar emit energy that bounces off the land or water surface and returns to the sensor to be recorded. The way the energy is directed or scattered by the surface, and the time it takes for the energy to return, reveals information about surface characteristics. Because of the long wave lengths employed by radar, the signals can penetrate clouds, thereby allowing scientists to record information about normally cloud-covered areas. This is an asset in tropical areas such as the Amazon River basin.

Passive sensors, on the other hand, typically rely on solar illumination of the Earth's surface, though some are equipped to detect night-time lights and gas flares. These sensors are "passive" because they do not emit their own energy, but rather rely on energy reflected or emitted from the earth's surface. Unlike radar sensors, they are unable to penetrate clouds. It is interesting to note that the visible portion of the spectrum—those wavelengths that humans can see—is a very small segment of the spectrum. Part of the strength of remote sensing is that it enables scientists to "see" portions of the spectrum that are outside the range that the human eye can detect. Scientists can combine non-visible portions with visible ones through color composites, assigning each *band* (or portion of the spectrum detected by the instrument) the colors red, green and blue.

Figure 2. The Electromagnetic Spectrum



Source: ICRSE, Remote Sensing Core Curriculum, Volume 2, Lecture 2.2.

A sensor's bandwidth and the number and placement of bands (within the spectrum) define its *spectral properties*. Panchromatic sensors measure reflected energy in a single portion of the electromagnetic spectrum, usually the visible to near-infrared regions. Multispectral sensors, on the other hand, collect reflectance information in discrete portions of the spectrum, with each being recorded as a separate image called a band or channel. When these bands are displayed on a computer, with one band shown through each of the blue, green and red channels of the monitor, they yield a combined color image. Landsat 7's Enhanced Thematic Mapper, for example, is a multi-spectral instrument that collects data in eight bands – three visible (one each for blue, green, and red), a near-infrared, two middle-infrared bands, a thermal-infrared and a higher spatial resolution panchromatic band. By contrast, the Moderate Imaging Spectrometer (MODIS) collects data in 36 different spectral regions, and the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) is a hyperspectral instrument that collects data in 224 spectral bands. A table of sensors and their capabilities is included in Annex 4.

Ultimately, what a sensor measures is the intensity of radiation that actually reaches the sensor, which is termed the *at-satellite radiance*. Radiance values are commonly translated into digital numbers (DNs). The possible range of DNs varies between sensors, although ranges of 0-255 (for 8 bit images) and 0-1023 (for 10 bit images) are common, with higher values corresponding to greater brightness. Radiance is captured by a two dimensional array of picture elements, or *pixels*. A DN for a pixel in a specific band is determined by the intensity of the radiance captured for that particular portion of the electromagnetic spectrum. If space-based passive sensors were able to accurately, precisely and repeatedly capture the actual reflectance from a feature on the ground, regardless of the time of day, season or weather conditions, much of the hard work of image processing would be eliminated. But the reality is that the atmosphere scatters radiation that is reflected back out to space. Smoke, haze, clouds and humidity exacerbate the problem, and can block reflected energy entirely. Data from shorter wavelengths are more likely to be blocked or scattered by clouds or atmospheric particles, whereas images using sensors capturing longer wavelengths are less likely to be disturbed by atmospheric conditions between the sensor and the target object.

3.4 Platforms and Orbits

High-altitude remote sensing originated in the mid-1800s with aerial photography by balloon and, in at least one instance, the use of cameras attached to the underside of birds. Airplanes became the dominant remote sensing "platform" by the early 20th century. This practice continues to evolve for wartime, intelligence, commercial and government applications. An advantage of airborne remote sensing, is the capability of offering very high spatial resolution images (20 cm or less). The disadvantages are low coverage area and high cost per unit area of ground coverage. It is not cost-effective to map a large area using an airborne remote sensing system. Airborne remote sensing missions are often carried out as one-time operations, whereas earth observation satellites offer the possibility of continuous monitoring of the earth. The development of satellite remote sensing had greatly improved the ability to cover large areas. (For details on historic development of satellite remote sensing and the various platforms and sensor systems, please refer to NASA's Remote Sensing Tutorial and a section by John Estes in the Remote Sensing Core Curriculum.)

There are two groups of satellites depending on the orbit in which they are placed. A *geostationary* orbit is established when a satellite is placed at a very high altitude, roughly 36,000 km above the earth's equator, and caused to orbit with the earth's rotation (called a *prograde* orbit). The altitude may vary slightly from one geostationary satellite to the next, depending upon the mass of the satellite, but, for the most part, this is a fundamental physical constraint. The rules of geometry – that is, the sight line from the satellite's position above the equator to the farthest edge of the earth's sphere – dictate that geostationary satellites can only "see" limited area at any one time. The laws of physics and capabilities of engineering limit their spatial resolution to a range of about 1 to 10 square kilometers. The total image or scene size, known as the *field of view*, is often thousands of kilometers. Thus, unless a geostationary satellite spins or turns its optics, its view is necessarily fixed. This allows for continuous monitoring, and often a very large, synoptic view of much of one entire hemisphere. The coarse (km range) resolution versus the wide, continuous field of view constitute the main tradeoffs to consider for this orbit type. These characteristics make geostationary satellites best for collecting weather and climate data (such as cloud cover and surface temperature) and relaying communications data, although AVHRR data are used for global- and regional-scale land cover analyses.

The other group of satellites, by far the largest group of earth-orbiting satellites is with the *sun-synchronous* or *polar-orbiting*. These are lunched below the altitude of geostationary satellites closer to the earth's surface, at orbits ranging from 700km to 1000km. These satellites usually orbit at a steep inclination relative to the equator, in the direction opposite the earth's rotation, known as a *retrograde* orbit. When the satellite's orbit and earth's rotation are combined, they result in an s-shaped path relative to a map of the earth's surface. Given enough time, the orbits and rotations of the earth bring the satellite over the same location, leading to the term *exact repeat* satellites. The number of orbits between each return to the same longitude and latitude is called the *repeat cycle*. These satellites usually orbit the earth in roughly 100 to 120 minutes, circling several times per day, returning a satellite to the same position over the earth's surface only after 2 weeks or more. The speed of motion limits the time that a satellite spends over a location, and the amount of time a scanner can "look" at any single ground cell (called the *dwell time*). Most exact repeat satellites that use passive sensors are also in sun synchronous orbits, meaning that they cross the same latitude at the same daylight time with each orbit, but with their location shifted to a different longitude. Their lower altitude allows these satellites to obtain images with spatial resolution ranging from 1-200 meters per side of a pixel, and an image width ranging from tens to thousands of kilometers per scene.

As the satellite passes over the earth's surface, its motion can be described in terms of a ground track that it follows at a certain altitude. Most satellites are *nadir looking*, meaning that their sensing equipment is aimed straight down toward the center of the earth. However, normal measurements generally include areas substantially on either side of this ground track, and that total area is called the *swath width*. Because most low-orbiting satellites follow a polar orbit, their ground tracks, and thus their swaths, are spread furthest apart at the equator, and are compressed at the poles. As a consequence, there is an overlap, called *side lap*, of neighboring swaths. Logically, this side lap is smallest at the equator and increased at the poles.

A basic understanding of ground tracks, swath widths, and side lap is helpful in designing a remote sensing experiment for a few reasons. First, weather and other temporary conditions may prevent good data acquisition for the first and/or "best" pass of a satellite directly over a given location. In this case, side lap may allow for multiple acquisitions of the same location on the surface with only a short delay, provided that the target location can be seen during two or more subsequent passes of the same satellite. This situation is more likely to occur if the sensing target is at high or low latitude than at the equator. Also, side lap may allow experimenters to obtain data for a single location in much more rapid time series than would be possible if the experimenters were to wait for the satellite to exactly repeat its path—a matter of hours, rather than weeks. Finally, side lap may allow the same location to be viewed from slightly different angles at slightly different times of the same day with neighboring orbital paths. This may provide additional information from shading caused by the sun's angle, and other factors that change with relatively small differences in position and time.

3.5 Sensor Characteristics

A sensor is characterized by its spectral properties (number and placement of bands), its orbital altitude and path, its swath width, and its *spatial resolution*. Spatial resolution is measured in terms of the size of one pixel projected on the ground. Spatial resolution is directly tied to the size of the features that can be resolved (or "seen") on the ground. The higher the resolution, the less likely that there will be "mixed pixels" in which radiances effectively represent an average of land cover types in the ground area represented by that pixel (e.g., half lake and half forest). Commercial high resolution sensors have a spatial resolution in the 0.6-10 meter range, medium resolution sensors fall in the 10-50 meter range, and low resolution sensors have greater than 50 meter resolution.

Until the advent of the commercial satellites IKONOS and QuickBird, with resolutions of one square meter or finer, high resolution imagery was the exclusive province of intelligence-gathering agencies. Most social science applications do not command the financial resources required to obtain such high resolution data, nor are images of this resolution generally required, except perhaps in the area of international relations, law and policy (see Section 5.4). Most social science research tends to utilize polar-orbiting satellites with medium spatial resolution, such as the Landsat, SPOT, TERRA and, more recently, AQUA satellites (see NASA's Destination Earth). They provide good spectral and ground resolution, with multiple visible, infrared, and panchromatic bands and pixel width ranging from 5 to 30 meters.

Table 1 summarizes the platform, orbit and sensor characteristics of the world's major satellite systems. More details on these and other satellites, the features they measure, and their uses in the social sciences are included in Annex A. An on-line source of information about sensor characteristics is Isciences' Guide to Current Sensors (see References).

Table 1. Characteristics of major Satellite systems

	IKONOS[1 †]	**SPOT[2]**	**Landsat[1 †]**	**TERRA (MODIS) [1 †]**	**AVHRR[1 † †]**	**RADARSAT[3r]**
Type:	Sun-synchronous	Sun-synchronous	Sun synchronous	Sun Synchronous	Sun Synchronous	Sun-Synchronous
Descending Pass:	10:30 a.m.	10:30 a.m.	9:45 a.m. * 10:00 a.m. **	10:30 a.m.		
Altitude:	681 km	832 km	920 km * 705 **	705 km,	833km	798 km
Inclination:	98.1 degrees	98.7		98.2 degrees	98.8 degrees	98.6 degrees
Period:		101.4 minutes	100	90 minutes	102 minutes	100 minutes
Repeat Cycle:	2.9 days at 1 m res. 1.5 days at 1.5 m res.	26 days	18 days * 16 days **	2 days	Twice daily	24 days
Spatial Resolution (in Square Meters)	1-4	10 - Panchromatic 20 - Multispectral	15 - panchromatic 30 - TM 80 - MSS	250 (bands 1-2) 500 (bands 3-7) 1000 (bands 8-36)	1,100 LAC 4,000 GAC	8-100
Swath Width	11 km	60 km	185 km	2330 km	2700 km	50-500 km
Archive	1999	1986	1972	1999	1978	1995

[1] United States, [2] France, [3] Canada, * Landsat 1, 2, and 3 Characteristics, ** Characteristics of Landsat 4, 5 and 7, [r] Radar

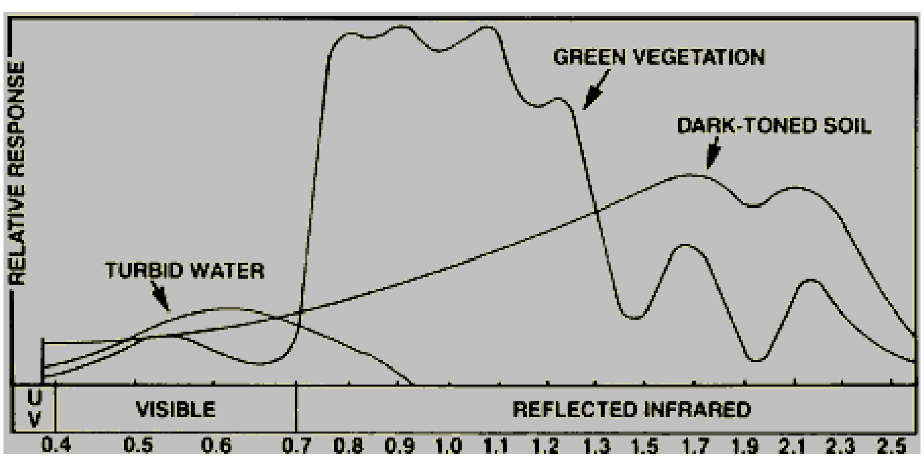
3.6 Data Processing, Interpretation and Analysis

Much of the technical work of remote sensing involves pre-processing and applying radiometric and geometric corrections to imagery to compensate for errors due to factors such as atmospheric interference of incoming radiation and sensor and data stream irregularities. Once such corrections are applied, imagery must be *georeferenced*. Georeferencing is the process of taking the image in its raw format (rows and columns of data) and linking it to the land that it covers. Images are georeferenced by linking spatially distributed control points in the satellite image to points on base maps or points referenced in the field through global positioning systems. The raster data in the image is thereby registered to a Cartesian coordinate system, and can be combined with other georeferenced data sets in a geographic information system.

The processed data can now either be visually interpreted or classified using manual or automated processes. The main elements of visual image interpretation involve gradients of tone or color, resolution, size and shape, texture and pattern, site and association, and height and shadows. Given their knowledge of the characteristic spectral signatures of different land cover types (Figure 3), scientists my inspect black and white images of each band separately in order to identify features and patterns.

For many purposes, data that is collected from the earth's surface, which represents a continuous variation, needs to be categorized (de Sherbinin *et al.* 2002). Image classification is the process of creating discrete classes or categories of land cover, utilizing information from some or all of the bands to group together pixels with similar spectral signatures. Supervised classification entails providing the software with sample pixels that represent specific features, such as boreal forest, and then having the computer classify every pixel with a similar *spectral signature* as boreal forest. Analysts may also use images from different seasons in order to discriminate vegetation cover types that have different phenologies, such as deciduous and evergreen forests. For an example of supervised classification, see Figure 4. In unsupervised classification, the analyst specifies the desired number of classes, and the computer automatically sorts the pixels according to their spectral signatures. The analyst then labels the resulting groups based on some local knowledge of the land cover patterns.

Figure 3. Spectral Signatures for Common Surface Types. *The spectral signature is the characteristic pattern of electromagnetic radiation that is obtained at the sensor from that land cover type across different portions of the spectrum. The numbers across the bottom represent wavelengths in nano-meters.*



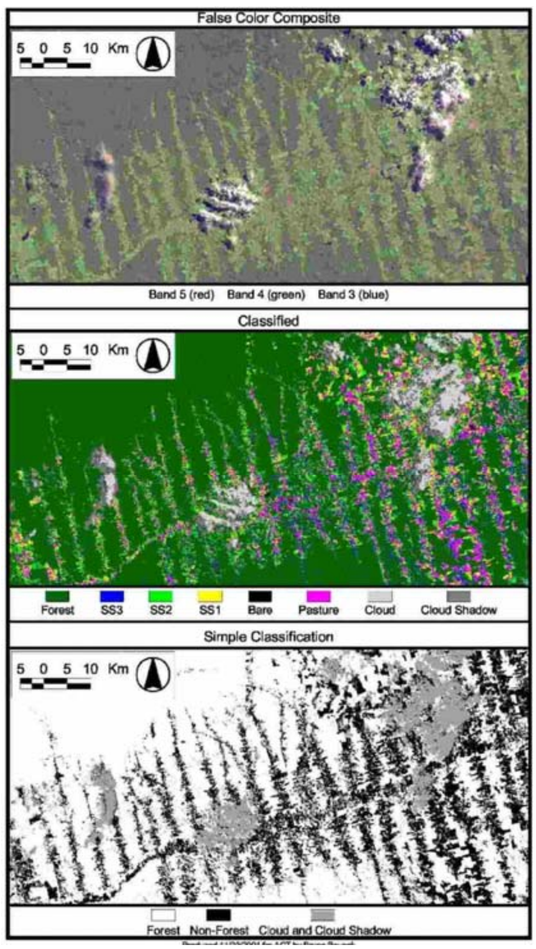
Source: USGS, Earth Shots: Satellite Images of Environmental Change.

Once classified, it is necessary to verify or validate that the output product accurately represents the actual composition, content, structure or land surface characteristics being mapped. Validation requires either field visits, ground-truthing or comparing the classified image with existing maps or images of sufficient detail. Statistics can be derived for the classified imagery indicating the general and specific (class-wise) agreement between the pixels or classes used, letting the user know which were classified correctly and which ones were not.

Validation results are also sometimes presented as a percentage value associated with the map that communicates how accurate the map is on a per pixel basis. Since the highest confidence rankings reported by satellite land cover data sets are between 85% and 90% (for the easiest types of land cover to classify), for an image with a per pixel accuracy of 85% the probability that one pixel out of four is incorrectly classified is close to 0.50.

The output of remote sensing data analysis can be presented in a variety of ways including a printout of the enhanced image itself, an image map, a thematic map (e.g. land use map), a spatial database, summary statistics and/or graphs (Jensen 1996). The output data can be integrated with a geographic information system (GIS) database for further analysis.

Figure 4. Image Classification of the "Fishbone" Deforestation Pattern in the Brazilian Amazon



Source: Anthropological Center for Training and Research on Global Environmental Change (ACT), Indiana University, in de Sherbinin et al. (2002).

4.0 – Remote Sensing and the Social Sciences

This chapter begins by examining how the use of remote sensing data can enhance social science research. It then proceeds to address several challenges to the application of remote sensing data in the social sciences: scale, data integration, interdisciplinary research, and confidentiality.

4.1 The Contribution of Remote Sensing to Social Science Research

Although remotely sensed data will rarely, if ever, completely supplant other sources of data in social science research, there are numerous ways that they can assist in answering research questions that are fundamental to the social sciences. One important contribution is the synoptic view from space that only remote sensing can provide. Remote sensing imagery can provide snapshots of phenomena over large areas, thus broadening the scope of social science inquiry. Examples include basin-scale analyses of Amazon deforestation, or scenes from space that pick up archaeological artifacts that are not visible on the ground or to the naked eye (Sever 1998). The ability of remote sensing to pick up and then represent parts of the non-visible spectrum in visible colors (red, green and blue) uncovers aspects of the natural and built environment that were previously opaque to social scientists.

Another advantage of the synoptic view is that scientists can “custom design” the spatial boundaries of their research. Political scientists, economists and others are often restricted to the use of national-level data sets. Remote sensing allows scientists to observe, and perhaps to understand certain processes that transcend national boundaries, such as cross-border social networks or patterns of trade and interaction (Blumberg and Jacobson 1997). As cross-border flows increase in the age of globalization, remote sensing may represent an important means of tracking these flows, whether they be flows of raw materials, water resources, or other natural resources. Furthermore, data collected using a common algorithm can provide valuable, consistent and objective cross-country comparisons that would not be available through data collected by national agencies (e.g. Sutton and Costanza 2002).

Remotely sensed data may provide a cost-effective method to reduce, but not replace, expensive ground data collection. In many parts of the world, spatial data on roads or infrastructure, farm sizes, industrial activities, or any number of other variables visible from space are either not available or difficult to obtain. In other instances, an area may simply be inaccessible for reasons of political turmoil or armed conflict. In these cases, remote sensed data, utilized independently or entered into a geographic information system (GIS), may provide an alternative source of data. Another example would be land uses by individual farmers. Farm level surveys can be employed to determine the amount of land farmed and the proportions in different land-use classes (e.g., Marquette 1998), but this may be costly and potentially less accurate than overlaying farm property boundaries onto remote sensing images (e.g., McCracken *et al.* 1999).

Social scientists are often interested in how context affects human behavior (Rindfuss and Stern 1998). Important contextual variables for an analysis of what crop small holders are likely to grow might include the following: the world price for a commodity, the farm gate price, the distance to major markets, what other farmers are growing, and the soil type and quality. Remote sensing can provide important information on biophysical parameters such as slope, aspect, soil types, water bodies and vegetation cover, and, in some cases, infrastructure parameters such as roads, pipelines, or power lines, that can impact people’s decision-making or livelihood options.

Data derived from remote sensing can provide dependent variables for numerous studies of human impacts on the environment. Although such studies are often focused on land-use and land-cover change (deforestation, agricultural expansion, urban sprawl, etc.), remote sensing can also provide valuable data on other human impacts such as air and water pollution (point source and non-point source), ozone depletion, coral bleaching, and land degradation, among others. These variables are particularly important for human dimensions of environmental change research, and can be associated with a variety of independent variables such as government policies, technologies, and economic and demographic factors.

Remote sensing may provide additional measures of certain phenomena, which would allow social scientists to cross-check or complement their own data sources derived from field surveys, censuses or administrative records (Rindfuss and Stern 1998). Censuses, for instance, generally rely on household measurement of population. Identification of houses or new settlements from space can facilitate more accurate censuses (see Section 5.1). Measures of urban extent may be more accurately generated by remote sensing than by more traditional measures, such as official “city limits” based on administrative boundaries (see Section 5.6). Administrative records may provide parcel-level information that can be cross-checked against remote sensing images. The time series capabilities of remote sensing mean that these data can also be readily updated. These data may also be more consistent and freer from the kinds of bias that may are inherently part of data collected through survey instruments (Blumberg and Jacobson 1997).

Because many remote sensing scientists are trained in the natural sciences, social scientists who become experienced in remote sensing image interpretation can bring valuable insights to bear on the spatial patterns they see on the ground. Examples may include spectral differences in land use types that are associated with different forms of land tenure, or socially important distinctions in types of land use that may be masked by one land cover classification such as “forested” (e.g., oil palm plantation versus natural palms) (Rindfuss and Stern 1998).

4.2 Scale

Questions regarding the appropriate scale of research have become increasingly important in social science research. There is also increasing interest in linking scales, from local to global and global to local. As Gibson *et al.* (2000) point out, the natural sciences have long understood the importance of scale, but apart from perhaps geographers, social scientists as a whole have been less explicit, less precise, and more variable in their treatment of scaling issues. Here we address primarily issues of spatial scale, as opposed to temporal scale or hierarchies (taxonomy represents one kind of hierarchy, in which a species is also part of a family, phylum and kingdom).

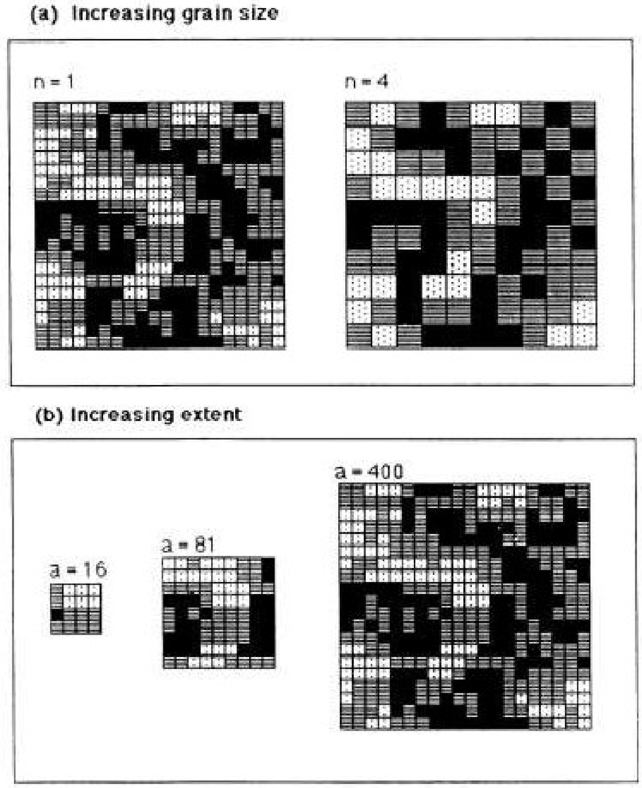
One of the first issues to be addressed in any discussion of scale is differences in terminology employed by different disciplines with regards to the use of the terms “large scale” and “small scale.” Cartographers and some geographers use the term to refer to map ratios; thus, 1:1000 is a *large scale* representing a small area, and 1:1,000,000 is a *small scale* representing a large area. All others tend to use these terms with precisely the opposite meaning. To the non-cartographer, a large-scale phenomenon is one that occurs over a large area, and a small-scale phenomenon is limited to a local area. Here we will use the terms fine scale for a localized phenomena and broad scale for phenomena at national, regional or global levels.

Remote sensing data come in a variety of spatial resolutions. The most commonly used data for social science applications are from medium-resolution sensors such as Landsat Thematic Mapper and SPOT, with approximately 20-30 meter ground resolution. Coarser resolution data, such as AVHRR (with 1 km grid cells), are sometimes used for broad scale analyses of countries or regions. The advent of higher spatial resolution (finer scale) commercial data (IKONOS and QuickBird, each with approximately one meter resolution) means that social scientists will have a much greater diversity of data to pick from, depending on the needs of their application. As shown in Figure 5(a), the resolution of the sensor can have a big effect on the variables that social scientists may be interested in measuring, such as the area or proportion of land found in different land-cover classes for the same geographic area. A higher resolution sensor will tend to more accurately reflect the actual extent of land-cover in any given class, and may produce a higher number of classes if, for example, one of the classes happens to occur only in isolated patches surrounded by other, more dominant, classes (e.g., small wetlands in forested areas). At lower spatial resolution (broader scale), the spectral signature of that pixel will reflect the most dominant class. Classes themselves are scale dependent, which is why the recently developed Land Cover Classification System (see References) has a hierarchical organization of classes, with higher-level categories appropriate for global land cover classifications and lower-level sub-categories appropriate for local or national mapping.

Landscape ecologists have long been aware of scale effects on standard measurements. Comparisons of landscape metrics using Landsat and AVHRR data for a heavily deforested area in Bolivia showed that both mean patch size and total edge length increased exponentially with decreasing spatial resolution (increasing pixel size) of the sensors (Millington *et al.* 2002). Similar work in Portugal confirms that the spatial resolution of the imagery has a strong effect on landscape metrics (Carrao and Caetano 2002). Thus, social scientists need to familiarize themselves with these scaling issues, and determine which resolution will yield optimal results for the phenomenon they are interested in. Highly heterogeneous or “patchy” landscapes will generally benefit from higher resolution data, with the trade off that such data generally cost more and may require longer processing times.

Figure 5(b) shows that if the area covered by a study is increased, the proportion of the landscape covered by different classes will be altered. If, in this example, black represents urban land uses, we see that the proportion that is urban goes from (left to right) 6 % to 32 % to 35 % solely as an artifact of the increasing area that is covered by the study. That is why it is important to have a clear rationale for choosing the extent of the study area (e.g., a watershed or an administrative area), and if the study is longitudinal, to be sure to retain the same extent over time. Simply choosing the “footprint” of the remote sensing image will not be an adequate approach, both because such a study area would be an artifact of the technology rather than a well-reasoned delineation based on social criteria, and because the footprint size can change over time as new sensors are introduced.

Figure 5. Illustration of (a) increasing pixel size and (b) increasing extent in a landscape data set



Source: Turner, M., R. O'Neill, R. Gardner, and B. Milne. 1989. Effects of changing spatial scale on the analysis of landscape pattern. Landscape Ecology*, Vol. 3, No. 3/4, pp. 153-162. With kind permission of Kluwer Academic Publishers.*

According to Gibson *et al*., "The crucial issue linking scale and level to explanation is whether the variables used to explain a pattern are themselves located at the same level as the pattern or at different levels." An example of a higher level variable operating at a lower level would be national-level legislation or price supports that affect a local-level phenomenon such as conversion of forest land for pasturage.

Researchers working with social science and remote sensing data must make important decisions about the level of aggregation of both remotely sensed and social science data. On the social side, the finest grain is the individual, and on the remote sensing side, the finest grain is the picture element (or pixel; progress has been made in mining sub-pixel level information) (Rindfuss and Stern 1998). Decisions on appropriate scale and how to aggregate are driven by theory and data availability. Social data may only be available at census tract or county level, which automatically limits the scale of research to those spatial units. Even these administrative units may vary greatly in spatial extent; for example, some counties in Texas are larger than entire state of Rhode Island. Furthermore, linking actors to what is happening on the ground can sometimes be difficult, especially if, as in the United States, people are highly mobile and commute long distances to work.

If one is not careful in one's understanding of scalar dynamics, it is possible to commit what is termed an "ecological fallacy." A textbook definition of ecological fallacy is "the danger of making an analysis at one level apply at other levels, for example, of inferring individual characteristics from group characteristics" (Mayhew 1997). Wood and Skole (1998) extend this definition to the spatial realm, writing that "the ecological fallacy can be thought of as a special case of spuriousness in which the relationships found in… regression analyses are due to a shared spatial location, rather than a causal connection." An example of an ecological fallacy would be the following. Say that population growth rates were found to be highly correlated with deforestation rates at the county level in a particular region, the researcher might conclude that population growth was a significant driver of deforestation. Yet, it may be that the population increased dramatically in urban areas contained within those counties, and that in fact the rural population, located where most of the deforestation occurred, remained relatively constant. This would be a form of spurious correlation; the real "culprit" might be something quite different, such as government policy or price mechanisms.

Aggregation can also mask important dynamics that are occurring at finer spatial resolutions. That is why some researchers are focusing on property-level dynamics of land cover change, linking household survey data to remote sensing images aggregated at the farm level (see CIPEC and Evans and Moran 2002; for more on this topic see Section 5.5 on land-use and land-cover change research).

4.3 Data integration

The difficulties of data integration include some of the scale issues described above, but extend beyond those issues to include problems related to georeferencing of social data, properly co-registering this data with the remote sensing data, and data quality.

Government-funded census and survey data are usually aggregated to census or administrative units that are well-defined, though they may change through time. Other variables of interest to social scientists, such as policies and market forces, also usually have an impact within defined administrative areas such as the nation state or a province within a country. For broad scale analyses, analyzing patterns in remote sensing images over the large areas that fall within administrative boundaries is relatively straightforward. Land-use/cover change matrices can be developed, air or water pollution levels can be understood, and other variables that may be of interest can be analyzed and clearly linked to the socioeconomic variables of interest. However, if one wishes to understand the specific factors that are affecting land-use decisions at a local level, a fine-scale analysis is required. For the most part, this will require surveys of land managers where they work or reside, and then, some kind of linkage needs to be made between the survey results and the actual land (identified in a remote sensing image) that is managed by the respondent.

Evans and Moran (2002) and Rindfuss *et al.* (2001) address this issue in some depth. According to Rindfuss *et al.*, a lot depends on whether the researcher starts from remotely sensed data of the land and seeks to link it to survey data, or from survey data and seeks to link it to landscape change. Regardless of the direction of the linkage, the researcher is confronted with the difficulty (especially in developing countries without extensive cadastral surveys) of correctly identifying and georeferencing the plot of land that the manager (whether owner, renter, or squatter) actually manages. Going to the field with a GPS unit is one approach, yet this is extremely time consuming, and will likely result in smaller sample sizes with possibly lower statistical significance of findings. Once the plot is georeferenced, it needs to be co-registered with the remotely sensed image in the Cartesian coordinate system. Co-registration in most cases is relatively straightforward. But in some instances, there may be difficulty in registering the remote sensing image in a Cartesian coordinate system because of a lack of ground control points (clearly identifiable features such as road intersections or sharp bends in a river). This spatial uncertainty would likely increase the error of any subsequent operations, such as overlay analysis in a GIS.

In some areas, there may also be a spatial mismatch between pixel size and plot size. Plot sizes may be smaller than the spatial resolution of the remote sensing instrument. High resolution commercial imagery, air photos, or aerial videography may be a solution in some instances, but for most studies their acquisition will be beyond the means of researchers.

Issues of data quality also arise. Even if there is no spatial mismatch, topographic shadowing in mountainous areas can render image interpretation more difficult, and necessitate the use of extensive (and expensive) ground-truthing. Cloud cover can also affect images, especially in the tropics, effectively rendering part of the study area opaque to researchers, especially in time-series analyses. Even with imagery that is relatively free of shadowing and cloud cover, positional and classification errors can arise in image processing (Evans and Moran 2002). Geo-referenced field data, also known as training samples, describing land cover conditions at specific locations, are necessary to reduce inaccuracies in land cover classifications. On the social science side, survey responses can be affected by who is present when the survey instrument is administered (if an oral survey), as issues of land ownership and management may be sensitive depending on the cultural context. Low match rates between the survey data and the remote sensing data may further affect the reliability of study findings.

One approach to facilitating data integration is to “grid” the socioeconomic data so that it better corresponds to the formats of Earth science data. This has been termed “pixelizing the social” (Geoghegan *et al.* 1998). CIESIN’s Socioeconomic Data and Applications Center (SEDAC) has developed a globally gridded population data set called Gridded Population of the World (see references; Deichmann *et al.* 2000). The methodology is to take population census data at the lowest administrative units available, and to transform them through an allocation algorithm to a grid of 2.5’ by 2.5’ latitude-longitude cells. A similar approach is being utilized for a global urban-rural data set. Landscan, a product of Oak Ridge National Laboratory, represents a product similar to GPW, but with additional algorithms to distribute population according to data on land cover classification, lights at night, slope, elevation and transportation infrastructure (Dobson *et al.* 2000). These gridded data can then be more easily combined with other data in models or analyses utilizing a GIS.

Another approach to facilitating data integration is to work in the opposite direction: to take Earth science data in gridded formats and to convert them to tabular data formats that are more useful or familiar to social scientists. SEDAC’s Population, Landscape and Climate Estimates (PLACE) data set is a first attempt to do this (see references). The methodology is to take remotely sensed data, or data originally derived from remote sensing instruments (e.g., elevation, slope, climate zones and biomes), and to develop national or sub-national aggregates of the territorial extent and human population that fall in various categories. These can then be combined with other tabular data aggregated at the national level, such as economic, environmental or trade statistics, to identify cross-national patterns through statistical analysis.

4.4 Interdisciplinary research

According to Rindfuss and Stern, “Integrating social science and remote sensing will require the fusion not only of data, but also of quite different scientific traditions.” Generally speaking, most integrative research has involved partnerships across disciplines. Traditionally, training in the social sciences has not emphasized remote sensing, though a new generation of spatially-oriented social scientists is increasingly learning spatial analysis and remote sensing techniques. The fact that few social scientists have in-depth knowledge of remote sensing and that few remote sensing scientists fully understand social science theories and methodological approaches has meant that partnerships are the generally favored approach.

Incentive structures are another hurdle, especially for junior researchers. Thus, even in partnerships scholars in one discipline may find it hard to convince their colleagues that the interdisciplinary work is relevant to the core of that particular discipline. As a result, they may not get “credit” for publications that arise from such research, especially if they are published in journals outside their discipline. This is a problem that is general to multidisciplinary research, and is not unique to social science applications of remote sensing.

4.5 Confidentiality

Social scientists have traditionally been concerned about the confidentiality of data provided by respondents. Such confidentiality protects the respondents from those who might misuse the data, and offers an assurance to research subjects that all reasonable efforts will be made to protect the link between their identities and the personal information they provide. Without such an assurance, many potential research participants would simply refuse to respond to surveys, interviews and other forms of questioning.

Even at moderate spatial resolutions (e.g. 30 m resolution), the possibility exists to identify residential locations for specific respondents (Rindfuss 2002). As higher resolution remote sensing data become available, there is an even greater ability to identify the precise location of individual dwelling units, and potentially material possessions and their location on the property. If the remote sensing image of a dwelling unit is coded and then linked to personal information from the respondents, it becomes a relatively simple matter for third parties to learn the identities of the research subjects. Government agencies, commercial entities or individuals could misuse this information. In societies with systematic human rights abuses, leakage of such personal information could be costly. High resolution imagery may lead to breaches of privacy even in the absence of ancillary social science data (Dehqanzada and Floriini 2000), since extensive information about household possessions may be obtained.

Rindfuss (2002) addresses this issue, and proposes several possible solutions. The first is to not collect spatially explicit survey data. This would have the unfortunate consequence of inhibiting the study of land-use decision-making. The second is to collect the data but not release it to the scientific community. This would inhibit scientific progress. One could also introduce random errors in the data, but this would affect the data’s accuracy. The classic solution, according to Rindfuss, is that traditionally used by census agencies, which is to aggregate the household or block-level data to higher units, such as census tracts. But this runs the risk of committing the ecological correlation fallacy mentioned above. A third solution is for the collecting institution to house the data, and to permit other researchers to access the data only by visiting the institution and signing some formal agreement to protect the confidentiality of respondents. While not failsafe, the ability to screen researchers should prevent the most egregious abuses. An additional solution would be one where technology allowed for distributed computing such that only the output data were revealed to the analyst, but such a solution is some years away.

5.0 – Applications in the Social Sciences

This chapter has six sections addressing the following research areas:

- demography
- human health and epidemiology
- archaeology and anthropology
- international relations, law and policy
- land use/cover change and sustainability trajectories
- urban studies

As mentioned in the introduction, there is a distinction that can be made between socially useful applications of remote sensing, such as in weather forecasting or urban planning, and the actual integration of remote sensing data in social scientific research. Our focus in this chapter is primarily on the latter. The following sections provide numerous examples where social science research has been informed by the use of remote sensing to understand patterns of land use, disease outbreak, population distribution and urban settlement. Still, there are a number of sections (such as the section on international relations, law and policy) where these distinctions may be harder to draw, and examples of socially useful applications are provided.

5.1 Demography

Many researchers have included demographic variables, such as population size, density, and distribution, or household characteristics, as independent variables to explain changes in land use and land cover. Most of the researchers in this area are not demographers, but tend to come from the fields of geography, anthropology, landscape ecology, and the natural sciences. A number of these studies are covered in greater detail in Section 5.5 on Land-Use and Land-Cover Change. Here the focus is on two areas:

- the use of remote sensing imagery to estimate population size, distribution, and quality of life; and
- studies that utilize remotely sensed imagery to understand patterns in the landscape, which in turn can inform population dynamics such as migration, fertility, and household formation.

5.1.1 Estimating Population Size and Quality of Life

Jensen and Cowen (1999) indicate that population estimates can be derived from (1) counts of individual dwelling units, (2) measures of urban extent, and (3) land-use/land-cover classification. According to the authors, remote sensing may provide population size estimates that approach the accuracy of traditional censuses provided sufficient *in situ* data are available. In parts of the developing world, where censuses are infrequent, remote sensing may provide a useful means of obtaining intercensal head counts.

The authors state that counting dwelling units is the most accurate method, provided the following criteria are met:

- The imagery must be of sufficient spatial resolution to identify individual structures even through tree cover, and whether structures are residential, commercial, or industrial.

- Some estimate of the average number of residents per dwelling unit must be available.
- Some estimate of the number of homeless, seasonal, and migratory workers is required.
- It is assumed that all dwelling units are occupied.

Much of this information can only be derived from extensive local knowledge and *in situ* observation. However, if these criteria are met, the results can be remarkably accurate. They report that a study in South Carolina utilizing 2.5 m resolution airborne multispectral data was able to estimate population for a 32 census block area with an r^2 of 0.81. In Nigeria, Olorunfemi (1984) found that 92 percent of the variation in population density could be explained by "housing" as a category of land use in Ilorin, Nigeria in 1950 and 1963. The areas in the housing category were detected using aerial photography. He then used a mathematical model to convert these land use data into population counts. Although such techniques are promising for individual cities or small areas at the sub-national level, the costs of applying this technique to an entire country are likely prohibitive (Sutton *et al.* 1997). It is worth noting that the estimates resulting from these techniques have not been evaluated in the demographic literature. Until they are, any such estimates will likely be viewed with some suspicion by professional demographers. The International Program of the U.S. Census Bureau is experimenting with the use of nighttime lights to estimate the population of countries lacking regular or reliable census data (Leddy and Mathur 2002) . In general, remote sensing is likely to be more successful in applications designed to allocate population density over a given land area where population size is known than it is in developing population counts themselves.

At a somewhat coarser level of analysis, Weier (2000) describes NASA-funded research utilizing the Defense Meteorological Satellite Program's (DMSP) Operational Linescan System (OLS) to detect nights at light. These data were then utilized to define the extent of urban areas (populated at over 1000 persons per square mile), peri-urban areas, and rural areas for the entire United States.

It has been suggested that remote sensing can also help to plan censuses by identify areas of new development, and to provide regular updates of new housing stock for local planners. Adiniyi (1987) explores visual interpretation of remote sensing imagery as a tool for census planning in Nigeria, especially as a means to identify enumeration areas.

In somewhat related work, researchers have sought to develop quality-of-life (QOL) indicators from remote sensing imagery. These indicators relate to vegetation cover and other metrics that provide proxies for the quality of life in urban and suburban settings. Lo and Faber (1997) utilized the normalized difference vegetation index (NDVI), produced with Landsat TM data, in conjunction with 1990 census data to measure quality of life of the Athens-Clarke County in Georgia. They found that greenness in the county was strongly correlated with income and median home value, and negatively correlated with population density. They conclude that the satellite imagery can provide a valuable environmental component to QOL assessments. In contrast to this work in Georgia, researchers focusing on Detroit (Emmanuel 1997, Ryznar *et al.* undated) find that increasing greenness is strongly correlated with indicators of social decay, such as poverty rates and child-to-women ratios. This appears to be related to population decline and abandonment of housing units. The difference between Athens Georgia and Detroit serves to underscore the importance of contextual information; if increasing greenness were used as a proxy for increasing affluence across urban areas of the United States, it might yield misleading conclusions. Pozzi and Small (2001) explore the patterns of vegetation and population density across a number of suburban areas in the U.S., and find that there are a wide variety of relationships.

5.1.2 Studies of Population Dynamics

There are relatively few demographers who have ventured onto the terrain of remote sensing to better understand population dynamics. As mentioned above, most research combining demographic data and remotely sensed imagery tends to view population as the independent, not dependent, variable. But in any complex, coupled system, it is possible for there to be two-way linkages. Land-cover changes can, in many cases, impact population dynamics. Desertification and land degradation, for example, have been posited to contribute to out migration to urban areas.

Weeks *et al.* (2000) use remote sensing to identify the location of villages in a study on fertility levels in Menoufia, Egypt. Although tabular data by village were available from the census, in order to add the spatial dimension to their research, they used IRS satellite imagery to classify the built area in the governorate, and then they assigned the village-level census data to the centroids of the polygons and incorporated the data into a GIS. Utilizing census data on fertility in a GIS with village location, they developed a model that showed that, in 1976, spatial clustering in combination with female illiteracy and proportion married explained about 39 percent of the variation in fertility in Menoufia. This increased to 51 percent in 1986. In 1986 about one-half of the explained variability was due to the spatial component. This suggested that diffusion of information among spatially clustered villages was an important element in the transition to lower fertility.

Entwistle *et al.* (1998) linked household survey data for communities in Nang Rong, Thailand, to remote sensing imagery from the 1970s and early 1980s for the areas surrounding those communities. In this area land is cleared to establish cultivation rights. For young farmers, access to land is vital if they are to be gainfully employed. A more fragmented landscape, with a large number of small forest patches, would suggest that there is a scarcity of land for the introduction of new crops. Preliminary analysis suggested that land fragmentation encouraged out-migration of young adults during the period from 1984-1994. Stated differently, districts with higher proportions of land in forest were less likely to experience out-migration.

Remote sensing has been applied in a variety of humanitarian crises (e.g., Bjorgo 2000, Kelly 1998, Lodhi *et al.* 1998), but there are relatively few studies that have examined the determinants and consequences of refugee flows from a social science perspective. Black and Sessay (1997) utilized a combination of air photos for 1980 and satellite imagery for 1991 to examine the environmental consequences of refugee flows from Mauritania to Senegal following a mass expulsion of approximately 60,000 Mauritanians in 1989. Although they found a net decrease in vegetative cover and an increase in cultivated area, they conclude that it is hard to separate out the impacts of the refugee camps from other social, political and climatic changes in the Senegal River Basin.

5.2 Human Health and Epidemiology

The use of remote sensing for the study of disease has grown rapidly in the past decade. The growth is attributable to several factors. Since the late 1980s, there has been growing use of geographic information systems (GIS) and spatial statistics in studies investigating patterns of disease incidence. Remote sensing was discovered to be a useful source of georeferenced data that, when combined with other data in a GIS, could help researchers to identify and understand

the environmental correlates of these patterns. GIS and remote sensing also help researchers to answer questions concerning the spatial and temporal aspects of disease outbreaks.
This section provides a brief introduction to the use of remote sensing in the study of human health and epidemiology. Sub-sections focus on mapping of current risk environments and the prediction of disease outbreaks through early warning systems. Readers desiring more information on the subject are recommended to read S.I. Hay, S.E. Randolph and D.J. Rogers, *Remote Sensing and Geographical Information Systems in Epidemiology* (2000), or to visit NASA's Center for Health Applications of Aerospace Related Technologies (CHAART) website.

5.2.1 Mapping Risk Environments

Remote sensing is primarily used in the context of disease mapping, in which statistical associations are demonstrated between ecological variables and processes that can be observed remotely (e.g., rainfall, temperature, vegetation cover, wetness, etc.). These, in turn, are correlated with vector distributions as well as disease incidence and prevalence (Hay 1997). The approach, sometimes referred to as landscape epidemiology, follows the following sequence: (1) remotely sensed data is used to provide information on land cover, and thereby habitat; (2) the spatial distribution of a vector-borne disease is related to the habitat of the vector; and (3) data on land cover, habitat and human population provide information on the spatial distribution of the disease (Curran *et al.* 2000, Landscape Epidemiology and RS/GIS). A knowledge of the likely distribution of vectors and the intersection with human populations can help make more efficient use of public health resources, in terms of spraying and eradication efforts, distribution of prophylactics and drugs for treatment, or location of health staff and facilities.

Curran *et al.* provide an excellent overview of the use of optical remote sensing data for health applications. They indicate that a complex set of inter-relationships exist between land surface characteristics, as perceived by remote sensing, and disease risk spatially distributed on the earth's surface. In the malaria-mosquito disease-vector combination, there is a link between land cover and vector density on the one hand, and vector density and disease risk on the other. In the case of the land cover and mosquito populations, it is generally understood that proximity to water is important, particularly in the breeding phase. However, there are many other factors that intervene, such as internal vector population dynamics, interrelations between the vector and vertebrate populations, and environmental influences such as microclimate. The relationship between vector density and disease risk is even more complex, depending as it does on dynamics within and between three populations: the hosts (vertebrates), the vectors (mosquitoes), and the disease itself. Mosquitoes live on the blood of vertebrates which may or may not carry the malaria parasite, and parasite-carrying mosquitoes may or may not transmit the parasite to the next vertebrate. The authors argue that future research in this area will need to move beyond simple correlations among land cover or vegetation indices and disease risk for mapping of risk environments, to a deeper understanding of the relationships among many complex factors.

Depending on the disease, the ability for remote sensing to accurately predict the actual distribution of disease vectors can be quite high. For example, Rogers *et al.* (1997) utilized vegetation and temperature indices from AVHRR data together with monthly rainfall indices derived from Meteosat to predict tsetse fly distributions in Cote d'Ivoire and Burkina Faso for the period 1988-92. Tsetse flies transmit trypanosomiasis, a disease that affects humans (as sleeping sickness), domestic animals and wildlife throughout much of sub-Saharan Africa. The spatial distributions of eight tsetse species were predicted with accuracies of 67 to 100 percent, with false positives (areas that did not have tsetse that were predicted to have them) of 12 percent and false negatives (areas that did have tsetse that were not predicted to have them) of only 3 percent.

Prediction of areas in which malaria is endemic can also be remarkably high. Malaria claims the lives of one million Africans annually, mostly infants and children. Because mosquito population dynamics and malaria incubation periods vary with temperature and moisture conditions, remotely sensed images of seasonal climate are good predictors of mosquito distribution patterns and average levels of transmission of malaria parasites by these vectors (Rogers *et al.* 2002, Hay *et al.* 2000). For East Africa, Omumbo *et al.* (2002) found that land surface temperature was a good predictor of transmission intensity, followed by rainfall and moisture availability (as inferred by cold cloud duration) and the normalized difference vegetation index (NDVI). Malaria-free areas were predicted with 96 percent accuracy. Areas where transmission only occurs near water were predicted with 90 percent accuracy, and intense malaria transmission areas were predicted with 87 percent accuracy. Using the above predictors, the researchers were able to update colonial-era maps of malaria distribution.

Kaya *et al.* (2002) explore the use of radar remote sensing for detection of mosquito breeding habitats, the principal vector for malaria, along the coast of Kenya. In many moist tropical areas, optical imagery is impractical to use because of the consistent cloud cover. Radar data have the advantage of being able to see through cloud cover to detect a variety of ground-cover types, including grasslands, forests, and wetlands. The researchers largely sought to identify the reliability of radar data for identifying land cover types associated with mosquito breeding areas, producing maps that showed potential vector density and not actual disease risk.

Another area of remote sensing application is tick-borne diseases. Ticks are both parasites, feeding off their hosts and weakening defenses, and vectors of disease (viral and rikettsial). Tick-borne Lyme disease is the most common vector-borne disease in the United States, and numerous tick-borne diseases exist in tropical countries (e.g. typhus and encephalitus). Tick distributions may be predicted by relatively straightforward statistical methods that seek correlations between environmental factors and tick presence (Randolph 2000). However, before distribution mapping can be undertaken, it is necessary to have good descriptive maps based on ground observations that identify known distributions of ticks. As with the case of malaria, remotely sensed indicators of moisture availability have accurately predicted the distribution of ticks (Liang *et al.* 2002). Tick survival rates decline significantly during periods of moisture-stress. Using remotely sensed land cover data, Dister *et al.* (1997) showed that suburban residential areas in New York state with high moisture and density of green vegetation had greater tick abundance.

Human helminth infections are prevalent in Africa and many parts of Asia. Estimates suggest that, globally, 1.2 billion people are infected with Ascaris lumbricoides, 1.2 billion with hookworm, and 200 million with schistosomiasis. The impact of these infections on human nutrition, education, and development, and the existence of effective anthelmintic drugs, has revived interest in their control (Brooker and Michael 2000). Helminth infections can be both directly transmitted (e.g., hookworm), and indirectly transmitted via an intermediate host such as snails (e.g., schistosomiasis) or mosquitoes (e.g., filariasis). A number of factors that can be detected by remote sensing are predictive of the spatial distribution of the infections, including temperature, distance to water bodies, soil moisture and humidity, rainfall, and altitude. Early work by Cross and Bailey (1984, cited by Brooker and Michael) found that presence or absence of schistosomiasis could be predicted with 87 percent accuracy in the Caribbean and 93 percent accuracy in the Philippines based on Multispectral Spectral Scanner (MSS) and weather data. In Cameroon, Brooker *et al.* (2002) used AVHRR data to predict the probability of helminth infection prevalence greater than 50 percent, which would warrant mass treatment for intestinal nematodes and schistosomes. By overlaying the risk maps on human population surfaces, they were able to estimate the school-aged population size requiring mass treatment. Seto *et al.* (2002) examine the use of Landsat TM data in predictive models to explore future schistosomiasis distribution in China as a result of global warming and completion of the Three Gorges Dam project (construction of canals will permit wider movement of snails). The work, which is still in progress, aims to produce predictive estimates of the distribution of schistosomiasis.

Tucker *et al*. (2002) utilize satellite data to study the poorly understood determinants of Ebola hemorrhagic fever outbreaks. Ebola emerged in Sudan in 1976, and although outbreaks have been limited in geographic extent and number of victims, it is characterized by gruesome symptoms (internal hemorrhaging) and high case fatality rates. They utilized Landsat data to understand the ecological setting and degree of human intrusion at the various Ebola outbreak locations. They also used time series NDVI derived from AVHRR data to understand precipitation regimes and wet season/dry season transitions associated with Ebola. They found that marked and sudden climate changes from drier to wetter conditions were associated with the Ebola outbreaks in the 1990s. A deeper understanding will only come from study of recent (Uganda 2000/01) and future outbreaks.

5.2.2 Challenges and Opportunities for Early Warning Systems

Although there is great promise in the use of remotely sensed data, verification of disease risk distributions by relating them to "real world" vector density or disease incidence data can be quite challenging. Often these data are either incomplete (especially in developing country contexts) or misplaced spatially from the location of disease contraction (Curran *et al.* 2000). Rogers *et al.* (2002) indicate that early warning systems require models that incorporate both extrinsic factors (e.g., climate) and intrinsic factors (e.g., immunity). Until analysts can properly assess the relative roles of both factors, however, it will not be possible to forecast outbreaks. The authors echo the lament of Curran *et al.*, indicating that researchers are hindered from making statistical predictions by the lack of good quality, empirically derived data sets for corroboration of satellite studies. The reason for this is that disease risks have been determined too infrequently, and over insufficiently wide areas.

According to Meyers *et al.* (2000), there are three components to an early warning system (EWS): (1) ongoing surveillance of the targeted disease; (2) modeling of the disease risk based on historical surveillance and contemporary environmental data; and (3) forecasting future risk through the use of predictive models and continued surveillance. In the late 1990s, researchers identified a need to move from risk mapping of current distributions to the modeling of vector population dynamics in real-time, utilizing remotely sensed correlates of life-cycle parameters (Hay 1997). The challenge was to combine near real-time remotely sensed data with information from climate predictions and other sources to create fully fledged early warning systems. These systems are beginning to make their appearance. Such systems necessarily draw on the expertise of social scientists, who are able to inform epidemiologists about local population distributions, land use and cultural practices that may influence disease risk.

The effort to track the West Nile Virus in the United States, and to predict likely future locations of disease outbreak, represents an early application of this kind of real-time monitoring and prediction (Rogers, *et al*. 2002). West Nile is transmitted by mosquitoes, with birds representing a significant host. Utilizing temporal Fourier processed land surface temperature (LST) imagery, the researchers were able to identify the annual means, amplitudes and phases of LST that best describe the thermal seasonality of habitats across the U.S. They combined this with satellite maps showing vegetation patterns and GIS-based data of bird migration routes and reported cases of the disease. The data sets help scientists predict disease outbreaks by showing where conditions are right for the insects to thrive and where the disease appears to be spreading, based on the right combinations of temperatures and moisture levels most suitable for mosquitoes and transmission.

NASA's Inter-agency Research Partnership for Infectious Diseases (INTREPID) has developed a dengue early warning system (DEWS) (Meyers *et al.* 2000). Dengue is a tropical disease transmitted by the *Aedis aegyti* mosquito which is particularly prevalent in urban areas and squatter settlements (owing to poor sanitation and an abundance of suitable mosquito habitat). The prototype receives data from Bangkok and four main regions of Thailand and contains several modules. The surveillance module allows new case data to be compared against the long-term average case data in order to determine the severity of current outbreaks against historical conditions. The risk map module translates case data into disease incidence data, which are in turn related to AVHRR satellite data using maximum likelihood methods to produce country-wide risk maps. The analysis helps to identify environmental variables determining local variation in risk. The forecasting module makes use of the time series data which show marked within-year and between-year cycles. Annual temperature changes trigger a series of processes that result in changing case numbers; thus, future cases can be predicted with some accuracy from current monthly temperature data.

The World Health Organisation Technical Support Network for the Prevention and Control of Malaria Epidemics suggests that population vulnerability assessment, combined with seasonal climate forecasts, weather monitoring and case surveillance can all be used for the development of effective early warning systems in epidemic prone areas where climate is an important component of interannual variability (WHO 2001). Such systems are currently being developed in Southern and Eastern Africa. The International Research Institute for Climate Predications at Columbia University is currently supporting efforts for the incorporation of seasonal climate predictions into operational actvities by malaria control services in Africa.

Others are exploring likely future distributions of vectors and diseases as a result of climate or land-cover change. According to Liang *et al.* (2002), "The ability to predict outbreaks months in advance based upon climate change indicators may make it possible to implement early vaccination initiatives or aggressive vector control programs and guide the relocation of human populations away from trouble spots… RS and GIS will likely enhance our understanding of the relationship between climate and vector-borne disease and prepare health professionals for changes in the distribution of important infectious pathogens." Warmer temperatures increase mosquito and tick vector reproduction, biting and pathogen transmission despite shortening survivorship, and have already demonstrably affected habitats for certain vectors. For example, malaria transmission is increasing due to changing climatic factors in areas where it had been hitherto constrained by low temperatures, such as the highlands of eastern and southern Africa (Lindsay and Martens 1998). Research suggests that malaria incidence rates also increase greatly during periods of high rainfall immediately following a drought. Proponents for Malaria Early Warning Systems in Africa have emphasized the potential value of climate predictions in areas where rainfall is the limiting factor to transmission (Conner *et al.* 1999, Thomson and Conner 2001).

5.3 Archaeology and Anthropology

The utility of remote sensing technology is becoming increasingly apparent to researchers whose work is aimed at obtaining a holistic understanding of the rise and development of human settlements occurring both in the past and present. Human ecology or landscape archaeology especially benefit from satellite data because such data can place local field studies within a regional context. The integration of satellite imagery, geographic information systems (GIS), data layers and fieldwork enhance the research possibilities and analyses by permitting the synthesis of environmental and ecological data with ethnographic, historic and archaeological research.

5.3.1 Archaeological Research

Remote sensing techniques had an earlier development in archaeology than anthropology. The use of aerial instruments for archaeological inquiry and survey was instigated by the work of Crawford and Lindbergh in the 1920s (Crawford 1928, Crawford 1929, Johnson 1930, Lindbergh 1929). By 1930, several archaeologists in Britain formulated methods and techniques of applying aerial photography in archaeological research (Wilson, 1982). The advantage of aerial instruments over ground field work was in that it allowed a much more rapid and territorial survey of the landscape for archaeological sites and features. This survey could be extended to a broader regional scale than permitted by foot and facilitated the detection of features such as crop marks, altered sediments, and linear or buried site features not otherwise visible from the ground. In most cases, remote sensing imagery is valued for providing a synoptic overview of the landscape and also provides a base map for archaeological research.

The remote sensing imagery utilized by archaeologists for decades became greatly enhanced with the availability of satellite imagery and image analysis software for archaeological inquiry. However, during the 1970s and 80s, the application of satellite imagery in anthropological or archaeological research was constricted due to factors related to the lack of technical expertise, the cost of imagery and the limited spatial resolution of early satellite sensors. In many cases, the low resolution of early satellites did not provide sufficient precision for the identification and inspection of archaeological sites. Nonetheless, a few leaders in the field including archaeologists Lyons and Avery (1977, 1981), through the National Park Service, were among the first to apply remote sensing technology in archaeological research with a project in Chaco Canyon, New Mexico. The project was the first archaeological project that fully embraced the application of remote sensing in its research methods and analysis. The archaeologists focused on the detection and analysis of a prehistoric Chacoan Roadway system dated between 900 and 1,000 A.D. In 1982, Thomas Sever, an archaeologist from NASA, expanded the research of the Chaco Canyon project with the use of TIMS (Thermal Infrared Multispectral Scanner). He detected a wide range of Chacoan infrastructure, including 300 kilometers of prehistoric roadways, prehistoric walls and buildings, and agricultural fields (Sever, 1987).

The Chaco Canyon project was quickly followed by additional archaeological projects established with NASA support. In 1984, an archaeological study using remote sensing was conducted in the Arenal region of Costa Rica (Sheets and Sever 1991). TIMS, SAR (Synthetic Aperture Radar), LIDAR (Light Detection and Ranging; a sensor used for gathering very accurate elevation data) and color infrared photographs were employed to detect pathways of prehistoric settlers documenting movement between settlements and trade routes. The detection of these distinct features with use of the imagery led to excavation that identified the period of use at circa 500 B.C. This research was a fundamental breakthrough in the application of remote sensing in archaeological research. Remote sensing facilitated exploration of the landscape and permitted the detection of archaeological sites and features not previously identified. Without the satellite sensor capabilities, the footpaths may have been left undetected due to the extensive overgrowth in the forests of these archaeological sites.

Since the work in the 1980s, there has been a steady increase of archaeological researchers using remote sensing data in their projects. Many researchers seek to comprehend the adaptations of communities in variable environments and how the social systems and patterns have shifted over time (Silbernegal et al. 1997, McCartney 1992). Madry and Crumley (1990) investigated land use patterns in France’s Burgundy region up to 2,000 years before present. Archaeologists have been able to detect the construction of agricultural features and determine the continued use, maintenance or desiccation of such features. Archaeologists may then hypothesize the social or environmental factors associated with such patterns (Lightfoot 1996, Pope and Dahlin 1989). In an archaeological study in Yemen, researchers found that abandonment of the Qatabanian irrigation canals in 200 A.D. was more likely due to neotectonic activity then social or political factors (Marcolongo and Banacossi 1997).

The applicability of satellite imagery in archaeological site analysis will vary in relation to specific site parameters, including consideration of the environmental setting and the archaeological site and feature characteristics (i.e. size, material, layout, pattern). In southern Madagascar, Clark *et al.* (1998) were able to detect archaeological sites from defined spectral signatures in the landscape that led to an analysis of the history of settlement patterns throughout the region. Satellite imagery has also been useful in the detection of certain environmental features conducive to archaeological sites such as peat deposits (Cox 1992).

Aside from the ability to expand the region of archaeological analysis with the use of satellite imagery, the variable spectral signatures emitted from archaeological features help to identify and characterize those features that may be buried or obstructed from sight. Many variables affect the visibility of cultural features on the ground including terrain, ground cover, weather, altitude and sun angles. Satellites are able to detect infrared radiation that helps discriminate different structural and linear features, revealing historic and prehistoric remnants either in the soil or vegetation. Synthetic Aperture Radar (SAR) was used in an archaeological project in the Taklamakan Desert, China (Holcomb 1992). Archaeologists were able to locate ancient watercourses, roads, forts and settlements established along the Silk Road that are now largely sand covered. Many features of archaeological interest can be easily detected with satellite sensors that help to quickly and precisely identify prospective areas of archaeological interest (Drager 1983).

Remote sensing will never fully replace the ground-based site survey as the ceramics and lithics often constitute archeological sites and are only visible from thorough ground survey. However, the integration of satellite imagery with ground fieldwork can expand the scope of reconnaissance in a region. Following the detection of surface and subsurface features in remote sensing imagery, a field validation survey would examine the archaeological site's feature characteristics and might lead to excavation. The satellite reconnaissance provides the archaeologist with a more efficient means of regional survey along with the production of base maps of natural resource data including the soil, vegetation, and hydrological elements of the region.

The advantages of satellite imagery as a data source for archaeological research include the systematic and frequent acquisition, synoptic coverage, digital data format, and archaeological features detection. Satellite imagery increases the rate at which an overall impression of the quantity, nature and distribution of archaeological features are obtained at a regional scale. Satellite imagery also expands the area of archaeological inquiry to regions with political, economic or physical barriers that may hinder access to sites. For decades, archaeologists researching the Homs region of Syria were unable to acquire aerial photos or maps at finer scales than 1:500,000. Recently declassified satellite images from the Corona satellite have made it possible to regionally review the area for changes in the landscape and increase the reconnaissance of archaeological sites (Philip et al. 2002). Certain constraints to systematic survey of an archaeological area of study such as cost, terrain or political unrest can be easily overcome with the use of satellite imagery. Despite the practicality and benefits of imagery in archaeological inquiry, there continues to be a significant absence of remote sensing applications within the field, largely due to cost, but also due to lack of technical expertise on the part of archaeologists.

One of the main deterrents in the acquisition and application of satellite imagery in archaeological and anthropological research continues to relate to cost. Beginning in 1972, the Landsat (Multispectral Scanner) MSS with 80 m resolution had limited value for the detection of archaeological sites. The Landsat 5 Thematic Mapper (TM), launched in 1982, with a resolution of 30 m opened more possibilities for research in this field. In the commercial sector, the IKONOS satellite was launched in 1999, and its imagery is available from Space Imagery Inc., with a resolution of 1m panchromatic and 4 m multispectral. QuickBird was launched in 2001, with a resolution of 0.61 m panchromatic and 2.4 m multispectral. These products are of value for the detection of archaeological sites and features, yet the costs can be high (as much as US $4,000 per scene depending on the amount of pre-processing requested). Nonetheless, as data sources proliferate, prices should begin to fall.

5.3.2 Anthropological Research and Land Use Studies

Understanding the social drivers of land use has become particularly important in today's global agenda of attaining environmental sustainability as articulated at the Earth Summit in 1992 (USGCRP 2001; see also Section 5.5 of this Thematic Guide). The interpretation of land use and land cover change dominates the research objectives of many public and private research institutions with over three decades of image acquisition allowing significant comparison of the spatial and temporal dynamics of the landscape. There has been considerable effort to link the physical and social sciences in the collaborative understanding of the dimensions of land use change and its impact on the future of the global environment (Haberl *et al.* 2001, Haberl and Schandl 1999,Veldkamp and Lambin 2001). However, two aspects of such an analysis largely neglected to date are the consideration of historical and cultural data that provide insight into the understanding of land use processes. Land use patterns are closely linked to the cultural practices shaping local and regional resource management practices, subsistence practices, landscape perceptions, and land use history. The integration of cultural and natural elements of land use facilitates a holistic modeling of past and present human settlement patterns.

Beginning in the 1970s within the field of anthropology, Reining (1979) and Conant (1978) conducted human ecology studies in Africa. Their studies were among the first initiated that linked ethnographic data obtained from local populations and the study of their subsistence systems with Landsat data. Although the importance of such integration was realized, issues related to technical expertise and access largely prohibited the anthropological community from broader involvement in remote sensing projects (Conant 1978). However, in the last decade, there has been a resurgence of anthropologists contributing to the understanding of land use processes by providing extensive ethnographic data on subsistence use and individual and household decision-making that influence environmental change (Moran 1993, Sussman *et al.* 1994, Nyerges and Green 2000, Stoffle *et al.* 1994, Behrens et al. 1994, Guyer and Lambin 1993). Anthropologists in the field obtain important cultural data relating to the motivations, perceptions, rationale and history of land use practices within communities. The ethnographic data can then be linked with the environmental change occurring, permitting a fuller understanding of the processes of land use change. This in turn helps to ascertain the future of the environmental resources within local communities.

The Anthropological Center for Training and Research on Global Environmental Change (ACT) specializes in interdisciplinary research on land-use change. Specialists at the center come from the disciplines of anthropology, ecology, geography, demography, political science and botany. The projects at ACT have been especially successful in applying remote sensing in research on the spatial and temporal dynamics of landscape change and identifying the social drivers of land use occurring in the Amazon, and increasingly in a number of other locations. Researchers at

ACT have been able to characterize the variable land-use patterns among Amazonian populations such as Caboclo communities, and to make conclusions about the environmental and community impacts of different patterns of land use, from subsistence farming to mechanized agriculture (Brondizio et al. 1994). Their research explores the factors affecting household strategies of land use that contribute to broader scale deforestation patterns (Moran 1993, Brondizio et al. 1994, McCraken 1999, Walker 2000). The research by scholars at ACT and elsewhere has firmly established the contribution of anthropological research in land-use and land-cover change research (Behrens 1994, Conant 1994, Sussman *et al.* 1994, Stoffle *et al.* 1994, Nygeres *et al.* 2000, Guyer and Lambin 1993, Lawrence *et al.* 1998).

5.3.3 Future of Remote Sensing in Anthropology and Archaeology

Continued progress in the development of sensor capabilities in terms of resolution and sensor features will enhance the research methods and potential capabilities for anthropologists and archaeologists. Several factors will contribute to the future implementation of remote sensing technology in anthropological and archaeological research including the improvement of satellite sensor resolution (especially the use of hyperspectral techniques), the building of image archives, facilitated access to data, and the acquisition of the technological skills in processing and applying the data.

The application of satellite imagery in archaeological research has been largely in relation to the detection and analysis of specific sites yet the potential of remote sensing imagery for use in site preservation has not yet been fully realized. The preservation of archeological sites is of considerable concern worldwide as they are placed under continual threat from both natural and social elements (Darvill *et al.*, 1993). Erosion, earthquakes and landslides have on occasion destroyed archaeological sites, while urban development, settlement patterns and infrastructure encroach upon others. The use of satellite imagery can provide identification of such ongoing or potential threats to archaeological sites.

The use of remote sensing in anthropology and archaeology is still in its early stages. The satellite sensors are just now becoming refined enough to allow more thorough investigations of the cultural processes occurring in landscapes, both past and present. Nonetheless, over the past few decades, the application of satellite imagery in anthropological and archaeological research has provided the means for investigation of former and present occupation patterns and resource use. Just as the work of archaeologists and anthropologists continues to contribute to the cultural and social interpretations of the environmental change captured in satellite imagery, there remains significant potential of remote sensing application in land use studies, historical ecology, human ecology, landscape archaeology and archaeological site preservation and management to further contribute to the understanding of the relationship between human activity and landscape development.

5.4 International Relations, Law and Policy

With the exception of meteorological satellites, applications of remote sensing technologies to international relations predate most Earth science applications. The earliest satellite remote sensing instruments, such as the United State's Corona and the former-USSR's KH, were high resolution sensors used for military and intelligence purposes. The focus of this section is on broader applications of remote sensing to international relations, and applications for domestic law and policy, rather than on military/intelligence applications. This is divided into the following subsections: diplomacy and arms control applications, crop monitoring and famine early warning, environmental treaties applications, and US domestic law and policy applications.

5.4.1 International Diplomacy and Arms Control Verification

The first reconnaissance satellite, Corona, was launched by the United States in 1960. The advantages of satellite reconnaissance over high altitude aircraft were apparent early on. Satellites could cover much greater territories in less time; they were unmanned, and therefore no personnel was put at risk; and it was not necessary to obtain the permission of countries for overpasses (Jasani 2000). It was only a matter of time before they were pressed into service as essential verification components to arms control treaties – all in an effort to keep “mutually assured destruction” from occurring.

Major nuclear weapons control treaties between the United States and the former Soviet Union (and current Russia) include the following: the 1972 Strategic Arms Limitation Talks (SALT) 1, the 1979 SALT II agreements, the 1987 Intermediate-range Nuclear Forces (INF) Treaty, the 1991 Strategic Arms Reduction Talks (START) I Treaty, and the 1993 START II Treaty. Two major approaches were taken to verification. One was co-operative measures, such as visits by weapons inspectors and the like. The second was national technical means, which included use of satellite imagery, aircraft-based reconnaissance, and sea- and ground-based monitoring systems (Schaper 2000).

Remote sensing is essential for building the confidence necessary in order to enter into nuclear weapons control treaties. Without the means to verify that the other party indeed reduced arsenals or destroyed production facilities as promised within a treaty, neither party would enter into such agreements in the first place.

Remote sensing may also have a role to play in monitoring of nuclear weapons tests. Jasani (1995) states that one of the major reasons for the failure to achieve the comprehensive test ban treaty (CTBT) was that states claimed it would be impossible to verify. However, he has conducted research in the use of Landsat imagery for identification of signatures that suggest a test is underway or has recently been completed. These include, for example, construction of roads, or tunnel construction, and land disturbances that result from nuclear tests around ground zero. Examples of the latter include craters, fracturing, and bulging of the earth’s surface. He argues that it is relatively easy to determine where tests have occurred based on such tell-tale signs.

Dehqanzada and Florini (2000) explore the implications of the availability of commercial, high spatial resolution satellite imagery for international diplomacy. In a world where only the superpowers possessed high resolution imagery, diplomacy was more predictable. Today, even the smallest states have access through the market place to one meter resolution imagery (e.g., IKONOS and QuickBird). This new democratization has advantages and disadvantages, depending on the perspective. For instance, high resolution imagery can be very useful to relief agencies in response to natural disasters, and it can uncover human rights atrocities through the detection of mass graves (in Bosnia) or destruction of remote villages by paramilitary groups. As with any technology, it has potentially harmful uses as well. State and non-state actors could use imagery to conduct espionage, collect intelligence, plan terrorist attacks, or mount military operations. The authors dub this an era of “mutually assured observation,” in which it will be harder for state and non-state actors to conceal their activities.

5.4.2 Agricultural Monitoring and Famine Early Warning

Remote sensing is used actively by the United States (and other countries) to monitor crop production domestically and in foreign nations. The purpose is to determine how crop production in these countries might affect the market for domestically-produced cereals. The US Department of Agriculture (USDA) Foreign Agriculture Service maintains a staff of remote sensing experts (see Remote Sensing: International Crop Condition and Production Analyses) who work year-round to estimate yields.

Remote sensing is used in measuring leaf area indices (a quantitative indicator of leaf stress), identifying soil properties by their spectral signals, evaluating crop productivity, and providing a valuable data source for crop simulation models (USDA Water Conservation Research Laboratory). It is also used for improved water management, especially in irrigation systems (Remote Sensing tools for Improved Water Management). Large scale agribusinesses in the US also use remote sensing for precision farming; based on remote sensing images of fields, farm equipment with GPS units apply precise amounts of fertilizer, pesticides and herbicides in order to optimize yields. In this regard, the airborne AVIRIS instrument, which measures over 300 spectral bands, is extremely useful for measuring soil moisture, plant infestations, and a wide variety of other parameters of interest to large-scale farming.

Famine early warning applications were examined by Hutchison (1998). An impressive amount of social science research has been directed to the study of famine and its determinants. This research has identified indicators that assist in monitoring food security. The Famine Early Warning System (FEWS), for example, identified three sets of indicators: (1) those that relate to food supply, (2) those that relate to food access (e.g., prices relative to local incomes), and (3) those that relate to levels of development and market access. Remote sensing has been used extensively for the first set of indicators. Relatively broad-brush analyses of likely crop yields can be developed from AVHRR imagery, and archives of scenes for the same period each year help analysts to determine if the yields are likely to be the same, better, or worse than average.

5.4.3 Environmental Treaties

Environmental applications have been a mainstay in the remote sensing field largely because many remote sensing scientists receive their substantive training in earth sciences and geography. The interest in remote sensing as a tool for the negotiation, implementation, monitoring and enforcement of environmental treaties stems from parallel developments in the areas of earth observation and international environmental diplomacy. On the one hand, instruments are being launched with ever more impressive capabilities, and vendors are looking for new markets. On the other, the numbers of treaties in force are constantly increasing (as of 1998 there were more than 350 treaties in force), and contracting parties are looking for easier ways to monitor their own and third party compliance (de Sherbinin *et al.* 2002, MEDEA 2002).

Many environmental treaties lack strong enforcement mechanisms. The ones that do provide for enforcement, however, have received greater attention from remote sensing scientists. An example of an application tied to treaty enforcement is the use of remote sensing for marine oil spill detection, which is currently taking place under the auspices of the Bonn Agreement among the nations bordering the North Sea. Under the Bonn Agreement, monitoring procedures have been set up to track oil spills to the ships of origin. Because oil slicks change the surface roughness of water bodies under the windy conditions that generally prevail on high seas, and this registers as changes in backscatter on radar instruments, SAR images have proven useful for spill monitoring (Jones 2001). The advantage of such monitoring is that it can cover much larger areas at lower cost than traditional aerial reconnaissance.

The Kyoto Protocol, when implemented, will require substantial data on greenhouse gas (GHG) emissions and carbon sources and sinks. Satellite sensors currently can measure carbon monoxide, methane, nitrous oxide and aerosols, but the technology is not at the point where it can easily inventory GHG emissions for a given country (these data are usually obtained from fossil fuel consumption and other proxy measures). However, remote sensing *can* provide valuable information on agricultural and forest land, which are important sources and sinks of carbon and other GHGs. Because the Kyoto Protocol makes provision for Annex I Parties (industrialized countries) to take into account afforestation, reforestation, and deforestation and other agreed land use, land-use change, and forestry (LULUCF) activities in meeting their commitments under Article 3, remote sensing applications are being developed that permit monitoring and verification of such activities (Rosenqvist *et al.* 1999). For example, the Global Monitoring for Environment and Security initiative of the European Commission is producing a number of experimental products that demonstrate remote sensing capabilities in support of Kyoto.

Although there is no forestry treaty *per se*, applications of remote sensing are well suited to forest cover monitoring, and such applications may in their own right have contributed to pressure on governments to limit deforestation. Brazil and other nations of the Amazon Basin are under considerable international pressure to limit deforestation in the basin as research shows the speed with which land conversion is taking place (Wood and Skole 1998, Nepstad *et al.* 1999, Sierra 2000). Global Forest Watch, a collaborative project to monitor deforestation in the world's remaining frontier forests – especially that which is taking place in forests that are supposedly protected – has made extensive use of remote sensing in its analyses of deforestation as it relates to land ownership status and forest concessions. It is likely that environmental watchdog groups will devise other applications for remote sensing in the detection and prosecution of "eco-crimes" such as illegal dumping of toxics.

A number of publications, workshop reports and links to related initiatives are available on this subject through SEDAC's Remote Sensing and Environmental Treaties website (see Related Resources). In addition, de Sherbinin and Giri (2000) have provided a summary of several pilot applications focusing on treaties related to biodiversity conservation, desertification, wetlands conservation, and marine and coastal environmental protection. Readers wishing to learn more about deforestation applications of remote sensing are encouraged to read the sections of the CIESIN Thematic Guide on Land-Use and Land-Cover Change that address deforestation.

5.4.4 US Domestic Law and Policy Applications

Remote sensing has a number of potential roles to play in domestic policy and legal realms. The following is a partial list of the types of legal problems for which remote sensing could play a part: discovery and assessment of taxable property; establishment of boundary lines in ownership disputes; appraisal of lands to be condemned under states' right of eminent domain; discovery and evaluation of the illegal deposition of fill dirt or waste materials on private property; auto, railway, and airline accidents; inventory of damages due to third party negligence; inventory of damages from fires, hurricanes, floods, and other disasters; evaluation of vegetation killed by noxious fumes from industrial point sources; verification of statements of fact related to the weather at the time of an incident (e.g., "it was raining hard at the time"); and natural resource damages from oil spills.

The reality is, however, that remote sensing imagery is seldom used in courts of law. Markowitz (2002) examines the reasons for the limited use, and concludes that the complexity of the information flow causes the data to become vulnerable to evidentiary challenges. Rules for admission of scientific evidence in the courtroom were established in Frye v. United States and Daubert v. United States, and among other things, these rules require that several criteria be met: (1) the scientific method must be adhered to, (2) the information should be subject to peer review, (3) the scientific community must "generally accept" the information, (4) error rates must be assessed, and (5) standards for operation of the technique must exist.

Markowitz explains that courts may warn against relying heavily upon remote sensing data because of the many transformations that data undergoes between collection and application and the potential for manipulation. He recommends that scientists and attorneys work together to identify specific applications and develop protocol for general acceptance of the information for the applied purpose. Efforts to educate the judiciary on probative values and science of remote sensing imagery is also critical. Such measures may ease courts' reluctance to work through the complex science and mathematics necessary to assign evidentiary value to the information. Further research is being conducted in this area by the National Remote Sensing and Space Law Center.

At the request of the US Senate Governmental Affairs Subcommittee on International Security, Proliferation and Federal Services, the Congressional Research Service conducted a survey of the applications of remote sensing by all federal agencies (CRS 2001). Of the 20 civilian agencies CRS surveyed, all but four use remote sensing data and technology in implementing their mandated missions. The application cited most often was for environmental conservation purposes. Seven agencies reported extensive to moderate use of remote sensing for early warning, mitigation, monitoring, and studying the impact from natural disasters. Other uses included basic and applied research, mapping activities, monitoring and verifying compliance with domestic laws and international treaties, agricultural activities, and transportation and shipping.

Remote sensing is also useful for the implementation of the National Environmental Policy Act (NEPA) of 1969, which requires an environmental impact assessment for all major federal actions. The same kinds of applications are relevant to multilateral and bilateral development bank financing, which also generally require environmental impact assessments.

In the aftermath of the terrorist attacks on the World Trade Towers in New York City, it is likely that law enforcement agencies will utilize high resolution remote sensing imagery for some domestic intelligence gathering efforts. Vogel (2002) proposes major investments in the National Spatial Data Infrastructure (NSDI) – including provision of remotely sensed data – to help communities to better prepare for terrorist attacks.

5.5 Land-Use Change and Sustainability Trajectories

Among the earliest social science applications of remote sensing were those addressing land-use and land-cover change. In these applications, time series land-use and land-cover data derived from remotely sensed imagery are used in conjunction with socioeconomic data to identify relationships between socioeconomic "drivers" (e.g., policies, demographic trends, economic factors) and changes in the landscape. Social scientists from a number of different disciplines, including anthropology, demography, economics, and geography, have been involved in this kind of research.

An excellent overview of research related to land-use and land-cover change is provided through CIESIN's Thematic Guide to Land-Use and Land-Cover Change (LUCC). The LUCC guide provides chapters addressing deforestation, desertification, biodiversity loss, climate change and the carbon cycle, the water cycle and urbanization (the latter is also covered in Section 5.6 of this guide). The focus of this section is more narrowly on the *remote sensing* applications utilized by social scientists in this area. Here we will focus primarily on land conversion from natural (largely forested) states to other land uses, and on use of remote sensing in conjunction with other data to identify sustainability trajectories.

5.5.1 Land Use Change

The greatest amount of research attention in the land-use and land-cover change arena has been dedicated to deforestation. Time series remote sensing imagery has been particularly valuable for this kind of research because conversion of forested land to other uses is, in comparison to other conversions (e.g. residential to commercial uses, or cropland to pasture land), fairly easy to detect. The most widespread application is simply to monitor the amount and rates of forest cover change between two time periods (e.g., the Forest Resources Assessment of the FAO).

To qualify as a social science application, there needs to be some attention paid to the social determinants of deforestation, and not simply the rates of deforestation. This generally entails the combined analysis of remote sensing and socioeconomic data. One approach has been to combine census data collected by administrative units with data from remote sensing satellites. For example, Wood and Skole (1998) used census data based on administrative units (municipios) in the Brazilian Amazon, together with forest cover change terms aggregated to those units, to identify and rank in importance the socioeconomic and demographic variables associated with forest clearing. They found little correlation between population density and deforestation, but when they added a variable for the number of migrants in rural areas, the r^2 increased significantly. Their model also included a proxy variable for conflicts between small land holders and ranchers, which was statistically significant, suggesting that such conflicts might increase the likelihood of land clearing to establish *de facto* ownership of land.

Pfaff (1999) combined aggregated forest cover change terms from remote sensing data and included both population and economic variables in his analysis of deforestation in the Amazon. The major empirical finding was the importance of land characteristics (soil quality and vegetation density) and factors affecting transportation costs (distance to markets and own and neighboring county road networks) in determining deforestation rates. Government development projects also appear to have an effect on deforestation, but access to credit and banking infrastructure does not. As with Wood and Skole, Pfaff's analysis did not find that population density *per se* had a significant effect on deforestation rates.

One problem with utilizing available data sets from census and other sources is that researchers might miss important causal variables that are not included in public data sources. Wood and Skole explore this issue, and suggest that one approach is to use models based on agricultural and population census data, and then to visit administrative units that are outliers in the model (those with large error terms) to identify what explanatory variables might be missing from their models. In this way the predictive model can be made more robust.

Another problem with using public source data is that, for confidentiality reasons, such data are usually aggregated to standard administrative units (such as county or census tract). In order for the social science and remote sensing data to correspond to one another, the remote sensing data need to be aggregated and analyzed at the same level (e.g. counties in the Amazon basin) (Rindfuss *et al.* 2001). This means that researchers lose the ability to pinpoint causal variables at a finer scale, such as decisions made by individual land holders or communities, to that particular pixel or group of pixels. In an ideal world, one would seek a much closer spatial congruence between the independent variable (e.g., the socioeconomic determinants) and the land cover changes occurring at the smallest spatial units available (e.g., the 30 m resolution of a Landsat TM pixel).

To address these problems, several research teams have invested significant resources in farm property and household level surveys, which then are linked to remote sensing imagery at either the same or higher levels. If the location of household plots are spatially registered using a global positioning satellite (GPS) unit, then linking this to the survey data and to spatial coordinates in the remote sensing image is relatively straight forward. This general approach has been used by Moran and Brondizio (1998) and McCracken *et al.* (1999) in the Brazilian Amazon; by Walsh *et al.* (2002) in the Ecuadorian Amazon; by Southworth and Tucker (2001) in Honduras; and by Entwistle *et al.* (1998) and Rindfuss *et al.* (2002) in Thailand. Each of these studies is briefly examined below.

In Moran and Brondizio's research, the remote sensing imagery itself is used to identify the potentially fruitful areas for field research. They chose Landsat scenes in which there was an identifiable soil and vegetation gradient, and with representative patterns of land use and population distribution. They then sampled within those scenes, choosing locations then going to the field to conduct detailed surveys of soil, vegetation and household characteristics. They discovered a high correspondence between soil fertility and rates of secondary succession; they were also able to identify economically important land uses that would have been invisible to a pure remote sensing image interpretation.

A team of researchers at the Anthropological Center for Training and Research on Global Environmental Change (ACT) overlaid a grid of property boundaries onto Landsat scenes for 1985, 1988 and 1991 in a GIS (McCracken *et al.* 1999). Analysis at the property level found patterns of land-cover classes that reflect differences in livelihood strategies of households. The overlay itself represented an integration of social data (property lines) with biophysical parameters (forest cover). This was supplemented with surveys of plots where unusual patterns were found. Through this work they were able to identify differences in land use patterns based on the life-cycle of the household (from young, nuclear families to older, intergenerational families). Younger families tend to clear land at higher rates initially, and to maintain more in annual crops, moving eventually into combinations of cropping and animal husbandry (grazing), whereas older, more established families have a more diversified portfolio of land uses. Furthermore, there is an important interaction between the life cycle and the initial conditions of soil fertility, with the families on richer soils having a more diversified portfolio than those on very poor soils. Thus, it is the interaction of demographic and biophysical variables that plays a significant role in the level of diversification of portfolios.

Walsh *et al.* utilize longitudinal survey data (1990 and 1999) coupled with remote sensing imagery (Landsat, SAR, and IKONOS) and GIS data layers of biophysical factors and transportation infrastructure to identify the determinants of agricultural extensification into the Ecuadorian Amazon, and to model future land-cover change. The strength of their research rests upon the longitudinal approach. The 1990 sample included 419 settler plots. These plots were revisited in 1999, and with the addition of sub-divisions and new households, the sample size grew to 767 farms (plus another 109 peri-urban parcels). Unlike McCracken *et al.*, the data on land cover characteristics for the parcels were not derived from remote sensing imagery, but from the farm-level surveys. The remote sensing data were used primarily to measure landscape-level changes in land cover, and to generate pattern metrics using Fragstats. As an indication of the rate of deforestation, in 1986 one-half of the landscape was still under high density forest cover; by 1996 the proportion was only one-third. Based on the survey data, they found that plots more distant from roads and in hillier terrain generally had a higher proportion forested. Household labor and presence of hired labor both had a negative effect on forest cover, while off-farm employment had a positive effect on forest cover. This rich data set also provides windows into livelihood strategies and a myriad of other research questions.

Southworth and Tucker's analysis in the county of La Campa in western Honduras combined 113 household surveys, 79 forest plot inventories, remote sensing for two dates (1987 and 1996) and 131 training samples (observations of land cover selected on the basis of image analysis). The remote sensing analysis revealed a net trend of reforestation. This was due in part to a county-wide ban on logging, conversion of communal lands to private holdings, and intensification of agriculture with simultaneous abandonment of less productive subsistence plots. Spatial factors such as topography and accessibility to road networks played a significant role in determining forest cover change. Although the remote sensing data were not linked to individual plots in this analysis, the household surveys provided important contextual information that assisted significantly in the analysis of the land-cover change data. The authors suggest that the reforestation trend in La Campa may in fact be transitional – privatization of land by a wealthier minority combined with population growth and trends towards market-oriented agricultural production (especially coffee) may increase pressures on remaining communal forest resources in the future.

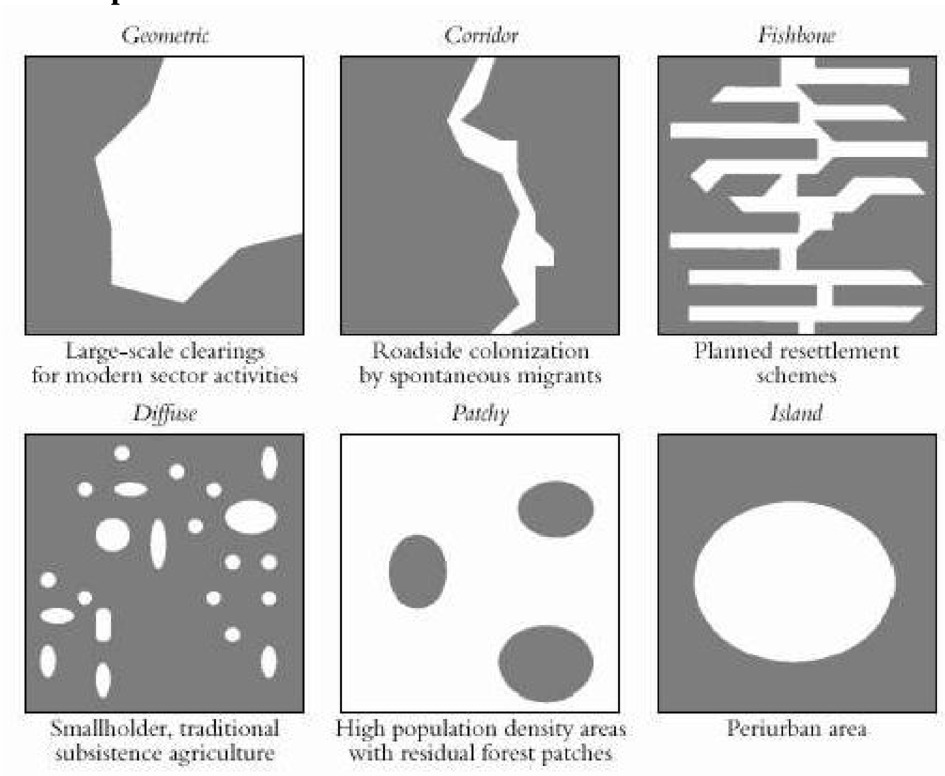
Entwisle *et al.* linked household survey data for communities to remote sensing imagery for the areas surrounding Nan Rong, a community in Thailand. At a first stage in their research, this community- rather than household-based approach was necessary because, unlike the Amazon, farmers tend to reside in clustered villages to walk to fields, which are dispersed in a patchwork around the villages. At a later stage, they invested considerable effort at one of their study sites in linking households to specific, georeferenced plots of land through utilization of maps based on remote sensing imagery and household and community interviews (Rindfuss *et al.* 2002). The pattern is complex because there are one-to-one, one-to-many and many-to-one relationships between households and plots of land. The research, which is still under way, will provide powerful insights into household decisions regarding land use, land renting, migration, and labor supply, as well as information on social networks and the diffusion of innovations.

There have been fewer attempts to link remote sensing and socioeconomic data for the study of other land-cover conversions, e.g. from productive subsistence agricultural land to “degraded” land, or from natural vegetation and agriculture to urban land uses. Xu *et al.* (2000) studied the impact of urbanization on arable lands in Fujian Province using a combination of remote sensing, census and economic data. They conclude that the region’s rapidly growing economy, with a Gross Provincial Product of 2.0 billion yuan in 1990 that increased to 13.5 billion yuan in 1996, was primarily responsible for the growth in urban extent from 4,495 to 7,864 km^2 during the same time period.

Millington *et al.* (1999) utilized Landsat TM and MSS imagery from 1972 through 1992 to analyze land use in an arid to semi-arid region in northern Jordan. Their time series data showed a distinct increase in the amount of rainfed and irrigated cultivation over the time period, which in turn was linked to population increases and government policies. They note that identification of rainfed fields was made more difficult by the spectral similarity between these and stone-strewn lava-flow surfaces and rangelands.

Finally, there has been some attention to the link between the social processes of deforestation and the spatial patterns of deforestation that appear on the ground. Geist and Lambin (2001) summarize the research in this area based on a statistical analysis of deforestation case studies (a more in-depth review of their work is found in Section 3.2 of the LUCC Thematic Guide). The results of their analysis are shown in schematic form in Figure 6. Moving clockwise from upper left, the *geometric pattern* of deforestation is commonly associated with large-scale clearing for commercial agriculture, large scale pasture, or industrial forestry plantation settlements. The *corridor pattern* of deforestation occurs in areas of roadside colonization by spontaneous migrants, and is commonly driven by road extension. The *fishbone pattern* is only found in the Brazilian Amazon, and is associated with planned resettlement, colonization, and transmigration. It represents a process of roadside frontier colonization. The *island pattern* is associated with periurban areas, and is related to semi-urban or urban settlements in forested areas. The *patchy* *pattern* is commonly related to high population density areas with residual forest patches, and is associated with permanent cultivation of food and to a lesser degree cash-crop production. The *diffuse pattern* is associated with traditional, small-holder subsistence agriculture, and in particular shifting cultivation and permanent cultivation by small holders.

Figure 6. Typology of the Forest-Nonforest Spatial Patterns and Their Interpretation in Terms of Deforestation Processes



Source: Mertens and Lambin (1997), reproduced in Geist, H. and E. Lambin. 2001. What Drives Tropical Deforestation?*, LUCC Report Series No. 4, Louvain-la-Neuve, Belgium.*

5.5.2 Sustainability Trajectories

Sustainability was defined by the World Commission on Environment and Development (Bruntland Commission 1987) as "the ability to meet today's global economic, environmental and social needs without compromising the opportunity for future generations to meet theirs." In the context of land-use and land-cover change, there is interest in understanding transitions in land use from sustainable states to less sustainable states or, conversely, from unsustainable practices to more sustainable practices. Remote sensing can provide a valuable tool by enabling researchers to examine large areas for "signatures of sustainability" or signs that the landscape may be entering a phase of "criticality."

Millette *et al.* (1995) examined three villages in the Kathmandu valley of Nepal for pathways to criticality, which they define as a regional situation in which the rate or extent of environmental degradation precludes the continuation of current human use systems or levels of human well-being, given feasible adaptations and societal capabilities to respond. They conclude that despite the difficulties of analyzing remote sensing imagery in a mountainous area where high slope angles and shadows complicate image analysis, remote sensing imagery in combination with ground-based data can "provide information highly germane to the analysis of changing nature society relations, including trajectories toward endangerment and criticality." However, they suggest that such studies still require detailed ground-based case studies; the imagery can then be used to further inform the case study, and to extend the analysis to wider areas, taking care that similar socioeconomic and environmental contexts prevail.

Although not explicitly developed as a "sustainability" study, Tappan *et al.* (2000) utilized a time series of declassified intelligence satellite data from the 1960s (Argon and Corona) in conjunction with Landsat imagery for the 1990s to analyze trends in land cover and soil fertility in the peanut basin of West-Central Senegal. The study covers 30 years, from 1963 to 1992, a period that saw significant demographic, economic, technological and cultural changes. The most striking land-cover change, they note, is the wholesale expansion of agriculture at the expense of the bushlands that made up the "commons" for grazing and firewood collection. Savannah woodlands and mangroves declined in aerial extent during this period, and soil conditions appeared to have deteriorated. They conclude that as the expansion of new cultivated areas is no longer possible, and the commons are no longer available for the production of needed goods and services, farmers will need to adopt new strategies of soil, water and vegetation conservation.

Based on a high correlation between night-time lights emitted and GDP, Sutton and Costanza (2002) developed a novel application of the Defense Meteorological Satellite Program's Operational Linescan System (DMSP OLS) data, which measures luminosity at night. Using luminosity as a proxy for economic activity, they mapped the location of major economic activities for each country and overlaid that map with another data set that measures the location of ecosystems services product (ESP). They found that among industrialized countries, smaller ones such as Belgium, Luxembourg and the Netherlands had a very small proportion (under 3%) of economic product derived from ecosystem services, whereas larger ones could attribute substantially more of their GDPs to ecosystem services (e.g. Australia at 67%, and the U.S. at 49%). For non-industrialized tropical countries, in excess of 90% of their total product could be directly or indirectly attributable to ESP. The authors compare these new measures with two existing measures of environmental sustainability, the Environmental Sustainability Index and the Ecological Footprint Eco-Deficit, and suggest that the spatially explicit nature of their data sets (developed on a 1 square km. grid) can permit modeling to characterize changes over time in the value of ecosystem services.

Turner (2001) describes advances in what he terms "integrated land science," in which "the environmental, human, and remote sensing/GIS sciences unite to solve various questions about land-use and land-cover changes and the impacts of these changes on humankind and the environment." The focus is on new and improved methods of detection and on predictive models, which fall in the categories of econometric, explanatory, agent-based or scenario-driven. The modeling efforts are bringing together researchers from disparate communities in the social and remote sensing sciences. He sees advances in integrated land science as being critical to the transition towards sustainability.

Although not yet operational, scientists at the Potsdam Institute for Climate Impacts Research are promoting the concept of a "Sustainability Geoscope" (see Sustainability Geoscope). According to its proponents (Lotze-Campen *et al.* 2002), the Geoscope will provide a framework for an observation and monitoring system on a global scale, comprising economic, social, environmental and institutional issues. Data sources would include a combination of satellite remote sensing, socioeconomic data and on-the-ground observations. The concept ties in with earlier proposals for a "syndromes approach" to global change research, in which a sample of areas is intensively monitored around the world for the identification of syndromes of unsustainability that can be addressed through concerted policy action (WBGU 1996). Syndromes are functional patterns of people-environment relations, characteristic negative constellations of natural and anthropogenic trends of global change and their respective interactions. Examples of syndromes identified include the “Sahel Syndrome”, “Rural Exodus Syndrome”, and “Waste Dumping Syndrome.”

5.6 Urban Studies

Population growth and urban expansion have advanced at an unprecedented pace over the past few decades. Although cities occupy only a very small portion of the Earth’s total land surface, almost half of the world population lives in urban areas (United Nations 2001). Urban growth has had increasingly significant socioeconomic and environmental impacts at local, regional and global scales (Berry, 1990). The rapid expansion of urban centers and their peripheries has led, in many cases, to a series of complex problems related to loss of agricultural land and natural vegetation, uncontrolled urban sprawl, increased traffic congestion and degradation of air and water quality. Such impacts affect not only the local environment, but also have consequences for more distant regions. Changes in vegetation cover, air and surface temperature and air and water quality induced by urban expansion influence the microclimate of the human habitat, as well as climate dynamics and environmental changes at local and regional scales. Urban growth has also significant impacts on the social structure of the cities and their surroundings, in terms of population distribution or land use characteristics. In addition to local impacts, the emergence of mega-cities (with more than 10 million people) is considerably influencing the social, economic and political systems on global levels, due the demographic and economic importance of such cities and their interconnectivity at large scales.

Consistent and efficient characterization of the urban environment provides the basis for urban planning and decision making, and facilitates the study of local and regional environmental processes in the broader context of global environmental change and the sustainability of cities and their hinterlands. Satellite systems can provide timely and accurate information on existing land use and land cover and have been increasingly used to characterize urban areas and to monitor urban changes in conjunction with socioeconomic and demographic changes. It is becoming more and more evident to both the physical and the social science research communities that remote sensing represents an essential tool in any environmental and socioeconomic analysis of urban areas.

The very first example of remote sensing in urban studies is represented by a camera carried on a balloon by Tournachon to study parts of Paris in 1858. Since 1948, when the full potential of aerial photography in urban analysis was examined (Branch, 1948), conventional black and white photography first, and color photography later, have been increasingly used in socioeconomic and demographic studies. Such studies were focused mainly on the use of photointerpreted data as auxiliary data sources for the census, or to predict socioeconomic variables such as poverty from housing density, structure type or vegetation cover. With the advent of the first generation satellite sensors (Landsat MSS) in the 1970s and the subsequent Landsat TM and SPOT, which were able to collect information in multiple spectral bands, including thermal infrared, virtually all research in urban areas focused on land use or land cover classification. Forster (1983) provides an extensive overview of early urban remote sensing applications.

This section of the guide discusses the following topics, providing examples of uses of remote sensing in urban analysis:

- Identification and delineation of the urban environment
- Classification of urban areas
- Measuring and monitoring physical properties of urban areas (vegetation, air quality, etc)
- Analysis of physical characteristics and demographic/socioeconomic patterns of the urban environment

- Monitoring changes and urban growth over time

The first three topics intrinsically address relatively technical issues of physical characterization of the urban environment and do not directly relate to social science applications. This background is important, however, for social scientists to be aware of, because it informs both the advantages and the limitations of remote sensing in the urban environment. The last two topics, on the other hand, report on studies that are clear social science applications.

5.6.1 Identification and Delineation of Urban Areas

Identification, delineation and classification of urban areas have typically been the realm of the technical remote sensing community. Much of the social and demographic information social scientists require can be more easily obtained from traditional government and private sector sources. Nonetheless remotely sensed data may provide a physically meaningful way to define urban areas that can then be utilized in social science studies.

The main problem in delineation of urban areas in the social science context is the lack of a consistent definition of what is urban. Definitions vary from country to country (United Nations, 2001) and are often based on different parameters. Urban areas may be defined by administrative boundaries, or by population density, and this varies from country to country. It is easy to understand the limitations in these approaches: the majority of urban areas have boundaries that don't coincide with administrative divisions, and defining cities based on a population density threshold that differs by country makes comparative studies more difficult. Furthermore, such approaches do not include spatial extents of built-up areas. Satellite imagery may be used to define urban areas in a more consistent way and to produce spatially georeferenced urban extents.

There is an extensive literature on urban delineation, although very often based on case studies of a single city, rather than on comparative studies. The book Remote Sensing and Urban Analysis (2001) contains several chapters dedicated to recent studies to develop new methodologies and algorithms to improve delineation and characterization of urban features, including integration with socioeconomic variables and applications related to urban growth modeling. Although quite rich in technical details, these chapters, and other publications, provide good examples of how remote sensing experts are implementing relatively new techniques to identify the different elements in the built-up environment based on their density and texture (e.g., Longley and Mesev 2001, Moller-Jensen 1990, Karathanassi *et al*. 2000).

A relatively new approach is one that looks at data fusion for urban analysis, which is based on the integration of data from different satellites, and with different spatial and spectral resolutions, to identify urban features, building types and building density (e.g., Proceedings of the IEEE/ISPRS Joint Workshop on Remote Sensing and Data Fusion over Urban Areas, 2001).

5.6.2 Classification of Urban Areas

If delineating urban areas is a difficult task, classifying different types of urban land use is even more so. The urban environment is characterized by a mixture of diverse material and land use classes, such as buildings, commercial infrastructures, transportation networks, and parks. Because they are combinations of spectrally distinct land cover types, mixed pixels in urban areas are frequently misclassified as other land-cover classes. Similarly, the definition of an "urban" spectral class will usually incorporate pixels of other non-urban classes. Such spectral heterogeneity severely limits the applicability of standard classification techniques, where it is assumed that the study area is comprised by a number of unique and internally homogeneous classes. Many authors (e.g., Welch, 1982, Forster, 1983, Forster, 1985, Jensen and Cowen, 1999) have discussed in detail the issues associated with spatial and temporal requirements for urban studies. For example, to be able to identify urban classes down to Level III of the Anderson classification system (that is, to differentiate between single-family and multi-family residential, for instance) a minimum ground resolution of 1-5 m is required. Commercial satellites, like IKONOS and QuickBird, as well as aerial photography, are being used for Level IV classifications (identification of duplex, triplex or condominium units), while satellites like Landsat will allow a Level I classification (Residential vs. Commercial, for instance). Higher spatial resolution normally comes at the price of lower temporal resolution and smaller areal coverages. For studies of urban growth or over large areas, such high ground resolutions might not be necessary.

Urban classifications are often improved by integrating satellite-derived classifications with ancillary data in a GIS environment. Ancillary data might include a range of socioeconomic variables, such as population or housing density, derived from the census or similar data sources or variables like land use and digital elevation models (Stefanov et al. 2001).

More recent techniques in urban classification rely on hyperspectral data. A hyperspectral image is one in which the radiance from each pixel is measured at many narrow, contiguous wavelength intervals. This enables identification of surface features, making hyperspectral sensors good candidates for mapping complex urban systems, particularly for classifications based on material composition. However, there are some limitations in their applicability for the social sciences. First, the majority of hyperspectral sensors have been airborne (e.g., AVIRIS, CASI, PROBE-1, AISA), with only two recent exceptions (NASA's Hyperion on EO-1 satellite and the US Air Force Research Lab's FTHSI sensor on the MightySat II satellite). This might limit temporal and spatial availability of data. Second, the image classification process might not be trivial, in that it requires good spectral libraries, which in many cases need to be created beforehand and, in some cases, complex sub-pixel analysis methods. For more information refer to the reports of AVIRIS workshops, available from 1990 to 2001 (AVIRIS Workshop Proceedings 2001) or to authors who used hyperspectral data to define specific urban land uses (e.g., Hepner *et al.*,1998, Ben-Dor 2001).

5.6.3 Measuring and Monitoring Physical Properties of Urban Areas

Urban areas exert an influence on local weather and climate, but they also affect wider regional and global atmospheric systems. Changes induced by urbanization include changes in solar radiation absorption, surface temperature, evapotranspiration, water vapor and pollutants concentration, which in turn link to human health problems. Remote sensing data is proving extremely useful for urban studies in terms of providing scientifically verifiable, routine measurements of physical properties that would be difficult or more expensive to obtain *in situ*, especially in developing countries.

The urban heat island effect, generally represented by the difference between urban and rural temperatures, has been studied since the 1930s. Many studies have addressed urban heat as a physical phenomenon (Oke 1973, Oke 1982) and attempted to quantify various aspects of maximum temperature differences and energy balances in urban and rural areas (e.g., Chandler 1964, Bornstein 1968). It is in the 1970s that use of remote sensing to assess the urban heat island effect was initially explored. Thermal measurements from satellites (such as TIROS or the NOAA 3 VHRR, at first, and AVHRR and higher resolution Landsat later) were used to delineate urban areas (Rao 1972) and characterize the urban heat island effect (e.g., Matson *et al*. 1978, Roth *et al*. 1989). In particular Roth *et al.* (1989) analyze the reasons behind the differences between remotely-sensed heat island and air temperatures measured using standard or mobile stations, and describe the utility of satellite data in urban climate models. Such differences are related to the urban geometry (over representation of roofs and tree tops), to the lack of simple coupling between the surface and the air in the urban system, and to the failure to recognize and consider the different scales of climatic phenomena in the urban atmosphere. There is a general agreement that variations in temperature associated with different land uses might prevent a clear delineation of possible urban thermal anomalies in some areas. For this reason, an increasing number of studies have been focusing on indirect measurements of the heat island effect. For instance, Gallo *et al*. (1993) observed a correlation between a vegetation index (NDVI) and observed temperature leading to the possibility of using NDVI as indirect measurements of the temperature variations. In another study, Gallo *et al.* (1995) suggest that a combination of NDVI and night-time lights might prove more effective in the evaluation of urban heat island effect. Another example of indirect measurements of heat island is the use of urban population growth as a predictor of the urban heat island (Karl 1988).

There are also numerous programs devoted to the study of the urban heat island effects and possible mitigation strategies. Global Environmental Management (GEM), for example, is an environmental technology firm specializing in energy efficiency and air quality solutions through Urban Heat Island Mitigation (UHIM) programs. The firm is also collaborating with the Global Hydrology and Climate Center (GHCC) at NASA Marshall Space Flight Center (MSFC) to commercialize NASA technology into products and services for urban environmental programs. Other examples are the Heat Island Program (HIP) at the Lawrence Berkeley National Laboratory (LBNL) and the EPA-NASA Urban Heat Island Pilot Project (UHIPP).

Other physical parameters measured include vegetation, ozone, dust and overall air quality in urban areas. Vegetation can substantially affect the wind, temperature, moisture, and precipitation regime of urban areas and is believed to have very important practical applications in urban planning, such as heating and cooling requirements of buildings, dispersion and concentration of pollutants, and urban weather (Avissar 1996). One interesting initiative related to the study of urban vegetation is the USDA Forest Service’s Urban Forest Research Unit (USDA 2000). Among other initiatives, such as studying the effects of urban vegetation on local and regional air quality, the Unit scientists have developed a model (the Urban Forest Effects-UFORE) to quantify urban forest structure and effects for cities across the country.

An example of the use of remote sensing for air quality monitoring is provided by the Center for Energy Studies (CES). The group uses Radar data to identify urban morphological features in relation with air circulation, and SPOT and Landsat data to study changes in visibility induced by air pollution.

Other parameters currently measured are ozone, dust, smoke and aerosol collected by NASA’s Total Ozone Mapping Spectrometer (TOMS), which provides long-term datasets of daily measurements over about two decades. The spatial resolution (in the order of magnitude of about 100 km at the equator) does not allow for a detailed characterization of air quality at the city level, but the data are extremely useful for global studies. The launch of the new Aura in 2004 will allow measurements of ozone, particulate, temperature etc, in the troposphere (from the ground to about 10 km), at a ground resolution of 12-24 km.

5.6.4 Analysis of Physical Characteristics and Demographic/Socioeconomic Patterns

Both social and physical scientists deal with the issue of integration of physical variables derived from remote sensing and traditionally collected socioeconomic and demographic data. Such integration might eventually lead to a better understanding of urban impacts and urban drivers of environmental and social changes, bringing benefits to both communities. Some of the past and on-going initiatives, especially in the remote sensing community, are focused on the integration of remote sensing with socioeconomic data to improve classification in urban areas (e.g., Harris and Ventura 1995, Mesev 1997, Vogelmann *et al*. 1998, and Chen 2001). Studies of this type show that classification of satellite imagery alone sometimes does not produce adequate results for specific urban applications. Remote sensing provides repeat coverages of a given area, allowing great data availability, but often at moderate spatial resolutions, while some ancillary data may provide levels of detail that are not available through the satellite data. Combining the two proves to be an effective way to reduce misclassification errors and improve the specificity of the final classification.

Other studies reflect the growing need of the social science community to use remotely sensed data in conjunction with demographic and socioeconomic data to study urban change dynamics or to better understand the spatial distribution of population and socioeconomic phenomena. Several authors studied the correlation between population data from the census, or collected from social survey at the village level, and land cover characteristics derived from satellite imagery (e.g., Yuan *et al*, 1997, Radeloff *et al*. 2000). In addition to examining the correlation between biophysical and social variables, Walsh *et al.* (1999) show the importance of scale dependence on the selected variables and that the relationships are not generalizeable across the sampled spatial scales. Lo and Faber (1997) present another interesting case, where their study of the correlation between environmental variables extracted from Landsat data and socioeconomic data from the census shows that a combination of satellite data and census data can be used to determine Quality of Life assessment with an environmental perspective (see also Section 5.1.1 of this Thematic Guide).

Research by Pozzi and Small (2002) looks at the correlation between population density (from the U.S. Census) and vegetation cover (extracted from Landsat) for a sample of cities in the United States. The authors show that for large cities there is a linear correlation between the two variables, but given the difference in resolution of satellite and census data, and given the different urban structures and growth dynamics, it is difficult to consistently characterize urban areas at the 30 meter resolution of Landsat imagery. Nonetheless, this can be considered an initial step towards alternative classification methods for urban areas, that look at the spectral heterogeneity of the urban environment, or at a combination of spectral and demographic data.

A noteworthy effort is the Long Term Ecological Research (LTER) Network (LTER 2001). Two of the 24 sites included in the program are urban areas: Baltimore and Central Arizona-Phoenix. The objective is to analyze the interactions of ecological and socio-economic systems and the effect of infrastructure and development on fluxes of nutrients, energy, and water in urban environments.

5.6.5 Monitoring Urban Growth

Monitoring urban growth is one of the questions social scientists, urban planners and decision-makers deal with most frequently. The direct impacts of urban expansion on physical, ecological and social resources have made research on urban sprawl of increased interest. Traditional census sources are extremely useful in that they capture changes in the socioeconomic and demographic structure of cities, but they lack spatial details and are not frequently updated. Remote sensing, on the other hand, makes available a vast amount of data with continuous temporal and spatial coverage and can therefore provide a successful means for monitoring urban growth and changes. Using remote sensing for change detection studies naturally requires that the different temporal images are atmospheric and zenith-angle corrected and carefully co-registered, in order to avoid errors in the estimation of land cover changes.

Despite the extensive literature of change studies available, most of these studies are based on more traditional land cover classifications (e.g., Wang and Zhang 1999, Esnard and Yang 2001, Stefanov *et al*. 2001), and only a few report examples of development of integrated datasets that can be used in planning and urban monitoring efforts. Examples of how remote sensing data can be used in conjunction with socioeconomic data are those of Emmanuel (1997) and Wagner and Ryznar (1999). They find that changes in urban vegetation can be linked to urban social changes in the city of Detroit, and suggest the development of an vegetation-based urban environmental quality index to monitor physical and social changes in cities.

Many cities in developing countries are experiencing rapid increase in population and consequential urban expansion. Remote sensing may provide fundamental observations of urban growth that are not available from other sources (e.g., Balzerek 2001).

An interesting project in the context of urban growth is Project Gigalopolis, developed at the University of California Santa Barbara and sponsored by the USGS Urban Dynamics Program. The project consists of a downloadable program for environmental simulation modeling of urban growth. The model is called SLEUTH, based on the simple image input requirements of the model itself: *S*lope, *L*and cover, *E*xclusion, *U*rbanization, *T*ransportation, and *H*illshade. The short-term objective of the model is to guide local community planners in achieving desired smart and responsible urban growth, while the long-term goal is to develop these tools to best predict urban growth on a regional, continental and eventually global scale.

The Urban Environmental Monitoring Project at Arizona University (UEM) has the objective of providing a dedicated observation strategy for urban environmental monitoring around the world using data acquired by the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). The project will study 100 of the World's largest urban centers, with an emphasis on those in arid and semi-arid environments. Studies will be done to monitor urban growth, land use change, impact on the surrounding environment, and the development of urban heat islands. The primary application of remote sensing data in this study is to provide a means for extrapolating detailed measurements at local sites to a regional context.

5.6.6 Recent Applications and New Developments

This section includes examples of new methodologies and applications that are currently being developed to gain better understanding of urban areas. For the most part such studies are still in the technical development phases and therefore limited to the remote sensing community. Nonetheless they are driven by social science questions and will certainly have very high potential to be applied in this field in the near future. Some of these efforts look at urbanization in a global context and attempt to provide a physical basis to standardize degrees of urbanization or urban extent.

The first area of new research is in the use of Spectral Mixture Analysis and linear mixture models to map urban extent and quantify physical properties (Small 2001, 2002a, 2002b). The dominant spatial scale of individual features (roads, buildings, etc.) in urban mosaics is generally 10 to 20 meters. Operational sensors like Landsat and SPOT do not have sufficient spatial resolution to discriminate individual features so most urban pixels image several different features with different reflectances. These mixed pixels are distinct from the more spectrally homogeneous pixels associated with most other types of land cover. Spectral mixture analysis and linear mixture models quantify these mixed pixels on the basis of the fractional abundance of different spectral endmembers (e.g., vegetation, water, high albedo). This provides a way to discriminate spectrally heterogeneous urban pixels from other types of landcover. It also provides a representation that is consistent with physical process models and environmental applications.

The second area involves the use of Shuttle Radar Topography Mission (SRTM) data to identify urban infrastructure (Nghiem *et al*. 2001). The data include derived topography and backscatter intensity at a nominal resolution of 30 m. Urban areas are generally characterized by very high backscatter intensity as a result of the abundance of corner reflectors (buildings). Some of the potentially derivable parameters include urban extent and boundaries, urban/suburban vegetation height and distribution, building height and volume, which could be used for various social science applications. In particular, if used in conjunction with data from other sensors (Landsat, AVIRIS), and from other sources (traditional census data), it may represent an excellent dataset to quantify economic development and transportation infrastructure, as well as to identify housing and other building stock.

The third area involves the application of time series data from the Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) to derive georeferenced inventories of human settlements (Elvidge *et al*. 1997a). The visible band of the OLS is intensified at night, permitting detection of nocturnal visible-near infrared emissions. The authors have developed a methodology to identify different light emissions sources and produced four separate datasets, at a nominal resolution of 1 km: Stable City Lights, Fires, Gas Flares and Lights from Fishing Boats. The city lights dataset has been used to explore the relationship between the area lit by anthropogenic visible-near infrared emissions and socioeconomic variables such population, economic activity and electric power consumption (Elvidge et al. 1997b). Others have begun to use the city lights dataset to map urban areas in the U.S. (Imhoff et al. 1997) to estimate the global human population (Sutton et al. 2001), and to develop a spatially explicit map of GDP (Sutton and Costanza 2002). Currently, CIESIN is utilizing OLS night-time lights data in combination with population data, high resolution spatial data and satellite imagery to derive a global dataset of populations and area extents for urban and rural areas. For more information on the Urban-Rural Database Project, see SEDAC's Urban Remote Sensing website.

Annex A. Satellites and Sensors

The following table lists the most known and used satellites and their sensors, with specifications about spectral, spatial, and temporal resolutions, what they can detect, and applications they can be used for.

Satellite	**Sensor**	**Spectral Resolution** (Wavelength in µm)	**Spatial Resolution**	**Temporal Resolution**	**What Can Be Detected?**	
					Spatial	**Temporal**
LANDSAT 4, 5 URL: *http://geo.arc.nasa.gov/sge/landsat/landsat.html*	**MMS** (Multispectral scanner system)	**1**: 0.5-0.6 (G) **2**: 0.6-0.7 (R) **3**: 0.7-0.8 (VNIR) **4**: 0.8-1.1 (NIR)	80 m; 185 Km swath width	16 days	Mapping coastal features in sediment-laden water Mapping roads and urban areas Vegetation studies and mapping land/water boundaries	Deforestation Urban and suburban development
	TM Thematic Mapper	**1**: 0.45-0.515 (B) **2**: 0.52-0.60 (G) **3**: 0.63-0.69 (R) **4**: 0.75-0.90 (NIR) **5**: 1.55-1.75 (Mid-IR) **6** (thermal): 10.40-12.5 **7**: 2.09-2.35 (Mid-IR)	30 m (visible, near and mid-IR); 120 m (thermal IR); 185 Km swath width	16 days	Soil/vegetation differentiation & coastal water mapping Vegetation mapping Plant species differentiation Biomass survey Snow/cloud differentiation Thermal mapping Geological mapping	Changes in heat islands Vegetation/land use patterns
LANDSAT 7 (1, 2, 3, 6 are inactive) URL: *http://landsat7.usgs.gov/*	**ETM +** (Enhanced Thematic Mapper)	**1**: 0.45-0.515 (B) **2**: 0.52-0.60 (G) **3**: 0.63-0.69 (R) **4**: 0.75-0.90 (NIR) **5**: 1.55-1.75 (Mid-IR) **6** (thermal): 10.40-12.5 **7**: 2.09-2.35 (Mid-IR) **8** (pan): 0.52-0.90	30 m (visible, near and mid-IR), 15 m (panchromatic), 60 m (Thermal Infrared); 185 Km swath width	16 days	Major Thoroughfares Large Buildings Forest Stands Agricultural Plots Coastline Advance/Retreat Rugged Topography Sea Ice Coverage	Changes in human infrastructure Development patterns Migration patterns Agricultural variations Urban/Rural interchange

Satellite	Sensor	Spectral Resolution (Wavelength in µm)	Spatial Resolution	Temporal Resolution	What Can Be Detected?	
					Spatial	Temporal
SPOT 1, 2, and 4 (3 is inactive) Launched by France from 1986-1998 **SPOT 5** Launched in may 2002 URL: *www.spot.com/*	**Two HRV-IR** (High Resolution Visible, Infrared) push-broom sensors. Provides coverage between 87 degrees north and 87 degrees south	1: 0.50-0.59 (G) 2: 0.61-0.68 (R) 3: 0.79-0.89 (NIR) 4: 1.58-1.73 (SWIR) – added on SPOT 4 Pan: 0.51-0.73	20 m (Visible, Near Infrared), 10 m (panchromatic); 60 Km swath width	26 days	Agriculture (Resource mapping, production management, crop classification) Land Use (Urban and suburban land use, land mapping, energy, human infrastructure) Oceanography (water quality management) Water resources (Surface water, soil moisture and evapotranspiration, lakes and rivers studies, wetlands and habitat mapping, resource assessment) Geological applications (mapping, economic geology, engineering geology, hazards and land morphology. oil and gas exploration) Engineering applications (terrain analysis, site investigation, water resources engineering, transport studies. Forest monitoring (inventory, forest management) and vegetation cover study (especially the VEGETATION sensor)	Deforestation Suburban/Urban land use changes Residential Development Coastal Pollution Water resource pollution monitoring Snow and Ice mapping Harvest forecasting Conservation monitoring Hazard prediction Landslide hazards Forest damage assessment
	High Resolution Geometry (HRG), the high spatial resolution version of SPOT 4 HRV-IR	1: 0.50-0.59 (G) 2: 0.61-0.68 (R) 3: 0.79-0.89 (NIR) 4: 1.58-1.73 (SWIR) – added on SPOT 4 Pan: 0.51-0.73	10 m (Visible), 20 m (Near Infrared), 5 m (panchromatic); 60 Km swath width	26 days		
	VEGETATION instrument (on SPOT 4).	1: 0.43-0.47 (B) 2: 0.61-0.68 (R) 3: 0.78-0.89 (NIR) 4: 1.58-1.75 (SWIR)	1 Km; 2200 Km swath width	Daily		

Satellite	Sensor	Spectral Resolution (Wavelength in µm)	Spatial Resolution	Temporal Resolution	What Can Be Detected?	
					Spatial	Temporal
IKONOS 1, 2 Launched in 1999 by the United States (IKONOS 2 failed) URL: *http://www.tbs-satellite.com/tse/online/sat_ikonos_2.html*	**MMS** (Multispectral) and PAN (Panchromatic)	1: 0.45-0.53 (B) 2: 0.52-0.61 (G) 3: 0.64-0.72 (R) 4: 0.76-0.88 (VNIR) Pan: 0.45 – 0.90	4 m (visible), 1 m (panchromatic); 11 Km swath width	26 days (680 km sun-synchronous orbit)	Roads, vehicles, buildings, infrastructure (panchromatic) Land use, agricultural uses, vegetation (color imager)	Changes in human infrastructure Development patterns Migration patterns Agricultural variations Urban/Rural interchange
Quickbird Launched in October 2001 URL: ***http://www.digitalglobe.com***	**MS** (Multispectral) and PAN (Panchromatic)	1: 0.45-0.52 (B) 2: 0.52-0.60 (G) 3: 0.63-0.69 (R) 4: 0.76-0.99 (NIR) Pan: 0.45-0.90	2.44 m (Multispectral); 61 cm (panchromatic); 16.5 Km swath width	1 to 3.5 days depending on latitude at 70-centimeter resolution	Roads, vehicles, buildings, infrastructure (panchromatic) Land use, agricultural uses, vegetation (color imager)	Changes in human infrastructure Development patterns Migration patterns Agricultural variations Urban/Rural interchange
NOAA - 7 Launched in 1981 and deactivated 1986 due to an power failure URL: *http://podaac.jpl.nasa.gov/sst/*	**AVHRR** (Advanced Very High Resolution Radiometer)	1: 0.58-0.68 (G and R) 2: 0.72-1.10 (NIR) 3: 3.53-3.93 (Mid-IR) 4: 10.3-11.3 (Thermal IR) 5: 11.5-12.5 (Thermal IR)	4.4 Km (Global Area Coverage), 1.1 Km (Local Area Coverage); 2800 Km swath width	2 times per day; 8-day and monthly averaged data available	Day and night cloud top and sea surface temperatures Ice and snow conditions	Changes in climate and global land and sea temperatures Changes in snow and ice coverages
AVIRIS Airborne Visible Infrared Spectrometer (instrument on board of planes) URL: *http://makalu.jpl.nasa.gov/aviris.html*	**Hyperspectral airborne sensor** Uses a scanning mirror in a "wisk broom" manner	Contains 224 different detectors each with a wavelength sensitive range of 10 nm, allowing it to cover the entire range between 0.4 and 25 µm.	20 m (high altitude), 4 m (low altitude); 11 Km swath width	Only scheduled flights	Ecology (chlorophyll, leaf water, lignin, cellulose, pigments, structure, non-photosynthetic constituents) Geology (mineralogy, soil type) Cloud and Atmospheric studies (water vapor, clouds properties, aerosols, absorbing gases) Oceanography/Coastal and Inland Waters (chlorophyll, dissolved organics, sediments, bottom composition, bathymetry) Snow and Ice Hydrology (grainsize, impurities) Biomass burning	Snow and Ice Hydrology (melting, snow cover fraction) Commercial (agricultural correction) Ecology (changes in vegetation and community maps) Oceanography (changes in plankton coverage and chlorophyll) Forest Fires

Satellite	Sensor	Spectral Resolution (Wavelength in µm)	Spatial Resolution	Temporal Resolution	What Can Be Detected?	
					Spatial	Temporal
					(smoke, combustion products) Environmental Hazards Commercial	
ERS2 (Active)	**AMI** (Active Microwave Instrumenta-tion) with SAR-Image Mode, SAR-Wave Mode, Scatter-ometer Mode and Radar Altimeter	5.3 GHz (C-Band) 13.5 GHz for the Radar Altimeter	30 m (SAR) 50 Km (Scatter-ometer); 80-100 Km swath width (SAR-Image mode); 5 Km swath width (SAR-Wave mode), 500 Km swath width (Scatteromet er mode)	3 day, 35 day or 168 day cycles	All-weather instrument Ocean wave height/lengths, wind speed/direction, ice parameters, sea surface & cloud top temperatures, cloud cover and atmospheric water vapor.	Alterations and observations in ocean, land, ice, atmosphere, and climate Flood activity Changes in ocean activity, coastal regions and ice caps
ERS2 (Cont'd)	**ATSR-M** (Along Track Scanning Radiometer with Microwave Sounder)	1.6, 3.7, 11, 12 (IR), 23.5 and 36.5 GHZ (Microwave)	1 Km (IR), 22 Km (Microwave); 500 Km swath width	3 day, 35 day or 168 day cycles	All-weather instrument Ocean wave height/lengths, wind speed/direction, ice parameters, sea surface & cloud top temperatures, cloud cover and atmospheric water vapor.	Alterations and observations in ocean, land, ice, atmosphere, and climate Flood activity Changes in ocean activity, coastal regions and ice caps
	GOME (Global Ozone Monitoring Experiment). Sensor is a double spectromete r	1: 0.24-0.295 2: 0.29-0.405 3: 0.40-0.605 4: 0.59-0.79	40 x 2Km 40 x 320 Km; 960 Km swath width			
	AATSR (Advanced Along Track Scanning Radiometer)	0.65, 0.85, 1.27, 1.6	0.5 Km; 500 KM swath width			
SEASTAR URL: *http://seawifs.gsfc.nasa.gov/SEAWIFS.html*	**SeaWiFS** (Sea-viewing Wide Field Sensor)	1: 0.402-0.422 2: 0.433-0.453 3: 0.480-0.5 4: 0.5-0.520 5: 0.545-0.565 6: 0.66-0.68 7: 0.745-0.785 8: 0.845-0.885	1.1 Km (local area coverage) 4.5 Km (global area coverage); 285 Km swath width	1 day	Ocean color and chlorophyll Subsurface scattering Atmospheric correction Atmospheric correction Sea-surface temperature	Changes in phytoplankton Designed to provide global coverage of the oceans on a regular basis

Satellite	Sensor	Spectral Resolution (Wavelength in µm)	Spatial Resolution	Temporal Resolution	What Can Be Detected?	
					Spatial	Temporal
TERRA Launched December 1999 URL: *http://terra.nasa.gov/About/*	**ASTER** (Advanced Spaceborne Thermal Emission and Reflection Radiometer)	14 bands, with wavelengths ranging from 0.52 to 11.65	15 m (VNIR), 30 m (SWIR), 90 m (TIR); 60 Km swath width	4-16 days By request	Major Thoroughfares Large Buildings Forest Stands Agricultural Plots Coastline Advance/Retreat Rugged Topography Sea Ice Coverage	Infrastructure Changes Residential Developments Deforestation/ Reforestation Harvest Flood Area Landslides & Mass Movements
	MODIS (Moderate Resolution Imaging Spectro-Radiometer)	36 bands, with wavelengths ranging from 0.405 to 14.38	250 m (bands 1-2), 500 m (bands 3-7), 1000 m (bands 8-36); 2330 x 10 Km swath width	1 to 2 days	Ideal for large scale changes in the biosphere, measures photosynthetic activity of land and marine plants Surface temperature measurements, Deforestation Forests, Open Canopy Vegetation, Large Scale Agriculture Water Clarity, Atmospheric Aerosols, Smoke Plumes, Snow Cover, Ocean Temperature	Forest Fires Regional Harvest/ Cycles Plankton Blooms Sediment Plumes Maps extent of snow and ice brought by winter storms and frigid conditions
	MISR (Multi-angle Imaging Spectro-Radiometer)	4 bands, with wavelengths ranging from 0.44 to 0.86	275 m; 360 Km swath width	9 days	The amount of sunlight scattered in the atmosphere under natural conditions, Atmospheric aerosol particles (formed by both natural and human activities) Cloud Cover/Type, Vegetation Type	Smoke Plumes Regional Air Quality Climate Regional Forest Canopy Structure
	CERES (Clouds and Earth's Radiant Energy System)	Shortwave: 0.3-5 Longwave: 8-12 Total: 0.3->200	20 km	Daily	Cloud/radiation flux measurements for models of oceanic and atmospheric energetics The cross track mode continues measurements of Earth Radiation Budget Experiment and Tropical Rainfall Measuring Mission	Contributes to wider range weather forecasting

Satellite	Sensor	Spectral Resolution (Wavelength in µm)	Spatial Resolution	Temporal Resolution	What Can Be Detected?	
					Spatial	Temporal
	MOPITT (Measure-ment of Pollution in the Tropo-sphere)	2.3 (CH_4) 2.4 and 4.7 (CO)	22 Km horizontally and 3 Km vertically; 640 Km swath width	3 – 4 days	Measurements of pollution in the troposphere Used to determine the amount of Carbon dioxide and methane in the atmosphere	
AQUA Launched May 2002 URL: *http://aqua.gsfc.nasa.gov/*	**MODIS** (Moderate Resolution Imaging Spectro-Radiometer)	36 bands, with wavelengths ranging from 0.405 to 14.38	250 m (bands 1-2), 500 m (bands 3-7), 1000 m (bands 8-36); 2330 x 10 Km swath width	1 to 2 days	Ideal for large scale changes in the biosphere, measures photosynthetic activity of land and marine plants Surface temperature measurements, Deforestation Forests, Open Canopy Vegetation, Large Scale Agriculture Water Clarity, Atmospheric Aerosols, Smoke Plumes, Snow Cover, Ocean Temperature	Forest Fires Regional Harvest/ Cycles Plankton Blooms Sediment Plumes Maps extent of snow and ice brought by winter storms and frigid conditions
	CERES (Clouds and Earth's Radiant Energy System)	Shortwave: 0.3-5 Longwave: 8-12 Total: 0.3->200	20 km	Daily	Cloud/radiation flux measurements for models of oceanic and atmospheric energetics The cross track mode continues measurements of Earth Radiation Budget Experiment and Tropical Rainfall Measuring Mission	Contributes to wider range weather forecasting
AQUA (cont'd)	**AMSR/E** (Advanced Microwave Scanning Radiometer)	12 channels and 6 frequencies ranging from 6.9 to 89.0 GHz (center frequency at 6.925, 10.65, 18.7, 23.8, 36.5 and 89.0 GHz)	Ranging from 56 km (at 6.925 GHz) to 5.4 km (at 89.0 GHz); 1445 km swath width	Daily	Cloud properties; radiative energy flux; precipitation; land surface wetness; sea ice; snow cover; sea surface temperature; sea surface wind fields	Contributes to weather forecasting and Climate Models
	AIRS (Atmospheri c Infrared Sounder)	2,300 spectral channels in the range of 0.4 to 1.0 and 3.4 to 15.4	13.5 km (IR) and 2.3 km (VIS/NIR); 1650 km swath width	Daily	Measures atmospheric temperature and humidity; land and sea surface temperatures; cloud properties; radiative energy flux	

Satellite	Sensor	Spectral Resolution (Wavelength in µm)	Spatial Resolution	Temporal Resolution	What Can Be Detected?	
					Spatial	Temporal
	AMSU (Advanced Microwave Sounding Unit) Consists of two sensors: AMSU-A1 ans AMSU-A2	15 discrete channels in the range of 50 to 89 GHz	40 km; 1650 km swath width	Daily	Measures atmospheric temperature and humidity	
	HSB (Humidity Sounder for Brazil)	4 channels: 1 at 150 GHz, 3 at 183 GHz	13.5 km; 1650 km swath width	Daily	Aimed at obtaining humidity profiles throughout the atmosphere	

References

Note that the full bibliographic information, URLs, and abstracts provided through the online CIESIN Thematic Guide to Social Science Applications of Remote Sensing are not provided in this brief list of citations. In addition, the online Thematic Guide has several hundred additional resources that are not directly cited in the text. *Go to http://sedac.ciesin.columbia.edu/tg/guide_main.jsp for full functionality.*

ACT: Anthropological Center for Training and Research on Global Environmental Change

Adeniyi, P.O. 1987. Geocarto International, Vol. 4, pp. 11-31.

Aerial Archaeology Research Group

Avery, T.E. and T.R. Lyons. 1981. Remote Sensing: Aerial and Terrestrial Photography for Archaeologists. National Park Service, Washington DC.

AVIRIS Workshop 2001, Pasadena, California, 27 Feb.-2 Mar. 2001.

Avissar, R. 1996. Potential effect of Vegetation on the Urban Thermal Environment. Atmosphere Environment, Vol.30, pp.437-448.

Balzerek, H. 2001. Applicability of IKONOS Satellite Scenes: Monitoring, Classification and Evaluation of Urbanization Processes in Africa.

Behrens, C. A., M. G. Baksh, and M. Mothes. 1994. A regional analysis of Bari land-use intensification and its impact on landscape heterogeneity. Human Ecology. Vol. 22, Iss. 3, pp. 279-316.

Ben-Dor, E. and H. Saaroni. 2001. A Spectral Based Recognition of the Urban Environment Using the Visible and Near Infrared Spectral Region. A Case Study over Tel-Aviv, Israel. International Journal of Remote Sensing, vol. 22, no.11, pp.2193-2218.

Berry, B.L. 1990. Urbanization. In: The Earth Transformed by Human Action, Turner B.L., W.C. Clark, R.W. Kates, J.F. Richards, J.T. Matthews and W.B. Meyer (eds), Cambridge University Press, Cambridge.

Bewley, R., D. Donoghue, V. Gaffney, M. van Leusen, and A. Wise. 1998. Archiving Aerial Photography and Remote Sensing Data: A Guide to Good Practice. Arts and Humanities Data Service.

Bjorgo, E. 2000. Using very high spatial resolution multispectral satellite sensor imagery to monitor refugee camps. International Journal of Remote Sensing. Vol. 21, Iss. 3, pp. 611-6.

Black, R., and M. F. Sessay. 1997. Refugees, land cover, and environmental change in the Senegal River Valley. GeoJournal. Vol. 41, Iss. 1, pp. 55-67.

Blumberg, D., and D. Jacobson. 1997. New frontiers: Remote sensing in social science research. The American Sociologist. Vol. 28, Iss. 3, pp. 62-8.

Bonn Agreement

Bornstein, R.D. 1968. Observations of the Urban Heat Island Effect in New York City. Journal of Applied Meteorology, vol.7, pp.575-582.

Brondizio, E. S., E. F. Moran, P. Mausel, and Y. Wu. 1994. Land-use change in the Amazon estuary - Patterns of Caboclo settlement and landscape management. Human Ecology. Vol. 22, Iss. 3, pp. 249-78.

Brooker, S., and E. Michael. 2000. The potential of geographical information systems and remote sensing in the epidemiology and control of human Helminth infections. In: Remote Sensing and Geographical Information Systems in Epidemiology, S.I. Hay, S.E. Randolph, and D.J. Rogers (eds.). Advances in Parasitology, Vol. 47, New York: Academic

Brooker, S., S.I. Hay, L.-A. Tchuem Tchuente, and R. Ratard. 2002. Using NOAA-AVHRR data to model human helminth distributions in planning disease control in Cameroon, West Africa. Photogrammetric Engineering & Remote Sensing, Vol. 68, No. 2, pp. 175-179.

Brooker, S; Rowlands, M; Haller, L; Savioli, L, and Bundy, D A. Towards an atlas of human helminth infection in sub-Saharan Africa: the use of geographical information systems (GIS). Parasitology Today (Personal Ed.). 2000 July;

Buchanan, J.T., and W. Acevedo. 1997. Defining the Temporal and Geographic Limits for an Urban Mapping Study. Proceedings, Urban and Regional Information Systems Association, Toronto, Canada, August 19-24, 1997.

Carrao, H., and M. Caetano. 2002. The Effect of Scale on Landscape Metrics. Paper presented at the International Society for Remote Sensing of the Environment conference, Buenos Aires, Argentina, 8-12 April 2002.

Center for Earth Observation

Center for Energy Studies

Center for Health Applications of Aerospace Related Technologies (CHAART)

Center for Remote Sensing

Center for the Study of Institutions, Population and Environmental Change (CIPEC)

Chandler, T.J. 1974. City Growth and Urban Climates. Weather, vol.19, pp.170-171

Chen, K. 2001. An Approach to Linking Remotely Sensed Data and Areal Census Data. International Journal of Remote Sensing, vol.23, no.1, pp.37-48.

Clark, C. D., S. M. Garrod, and M. P. Pearson. 1998. Landscape archaeology and remote sensing in Southern Madagascar. International Journal of Remote Sensing. Vol. 19, Iss. 8, pp. 1461-77.

Conant, F. P. 1978. The use of Landsat data in studies of human ecology. Current Anthropology. Vol. 19, Iss. 2, pp. 382-4.

Connor, S., M. Thomson, et al. (1999). “Forecasting and prevention of epidemic malaria: new perspectives on an old problem.” Parassitologia 41: 439-448

Congressional Research Service (CRS). 2001. Assessment of Remote Sensing Data Use by Civilian Federal Agencies, report by the Governmental Affairs Subcommittee on International Security, Proliferation and Federal Services, December

Crawford, O.G.S. 1928. Air Survey and Archaeology. Ordnance Survey Professional Papers, new series 7.

Crawford, O.G.S. 1929. Air Photography for Archaeologists. Ordance Survey Professional Papers, new series 12.

Curran, P.J., P.M. Atkison, G.M. Foody, and E.J. Milton. 2000. Linking Remote Sensing, Land Cover and Disease. In: Remote Sensing and Geographical Information Systems in Epidemiology, S.I. Hay, S.E. Randolph, and D.J. Rogers (eds.). Advances in Parasitology, Vol. 47, New York: Academic Press.

Darvill, T., Gerrard, C., and Startin, B. 1993. Identifying and Protecting Historic Landscapes. Antiquity 67(256):563-574.

de Sherbinin, A., and C. Giri. 2001. Remote Sensing in Support of Multilateral Environmental Agreements: What Have We Learned from Pilot Applications? Paper presented at the Open Meeting of the Human Dimensions of Global Environmental Change Research Community, Rio de Janeiro, 6-8 October 2001.

de Sherbinin, A., K. Kline, and K. Raustiala. 2002. Remote Sensing Data: Valuable Support for Environmental Treaties. Environment, Vol. 44, No. 1, January/February 2002.

Dehqanzada, Y.A., and A.M. Florini. 2000. Secrets for Sale: How Commercial Satellite Imagery Will Change the World. Washington, DC: Carnegie Endowment for International Peace.

Deichmann, U., D. Balk, and G. Yetman. 2001. Transforming Population Data for Interdisciplinary Usages: From Census to Grid. CIESIN Working Paper. Palisades, NY: Center for International Earth Science Information Network

Destination: Earth

Dister, S. W., D. Fish, S. M. Bros, D. H. Frank, and B. L. Wood. 1997. Landscape characterization of peridomestic risk for Lyme disease using satellite imagery. American Journal of Tropical Medicine & Hygiene. Vol. 57, Iss. 6, pp. 687-92.

Dobson, J. E., E. A. Bright, P. R. Coleman, R. C. Durfee, and B. A. Worley. 2000. LandScan: A global population database for estimating populations at risk. Photogrammetric Engineering & Remote Sensing. Vol. 66, Iss. 7, pp. 849-57.

Donnay, J-P, M.J. Barnsley and P.A. Longley (eds). 2001. Remote Sensing and Urban Analysis. London, England: Taylor & Francis.

Educational Pointers, Tutorials and Software

Elvidge C.D., K.E. Baugh, V.R. Hobson, E.A. Kihn, H.W. Kroehl, E.R. Davis and D. Cocero. 1997a. Satellite Inventory of Human Settlements Using Nocturnal Radiation Emisisons: a Contribution for the Global Toolchest. Global Change Biology, vol.3, pp.387-395.

Elvidge, C.D., K.E. Baugh, E A. Kihn, H.W. Kroehl, E.R. Davis and C.W. Davis. 1997b. Relation between Observed Visible-Near Infrared Emisisons, Population, Economic Activity and Electric Power Consumption. International Journal of Remote Sensing, vol.18, no.6, pp.1373-1379.

Emmanuel, R. 1997. Urban Vegetational Change as an Indicator of Demographic Trends in Cities: the Case of Detroit. Environment and Planning, vol. 24, pp.415-426.

Entwisle, B., S. Walsh, R. Rindfuss, and A. Chamratrithirong. 1998. Land-Use/Land-Cover and Population Dynamics, Nang Rong, Thailand. In: People and Pixels, D. Liverman, E. Moran, R. Rindfuss, and P. Stern (eds.). Washington, DC: National Academy Press.

Esnard, A. and Y. Yang. 2001. Descriptive and Comparative Studies of 1990 Urban Extent Data for the New York Metropolitan Region. Urisa Journal, accepted for future publication, version 10/16/01.

Evans, T.P., E.F. Moran. 2002. Spatial integration of social and biophysical factors related to landcover change. Population and Development Review, Supplement to Vol. 28, W. Lutz, A. Prskawetz, and W.C. Sanderson (eds.).

Forster, B. 1983. Some Urban Measurements from Landsat Data. Photogrammetric Engineering and Remote Sensing, vol.14, pp.1693-1707

Forster, B. 1985. An Examination of Some Problems and Solutions in Monitoring Urban Areas from Satellite Platforms, International Journal of Remote Sensing, vol.6, no.1, pp.139-151.

Fowler, M.J.F. 2000. In Search of History. Imaging Notes, Vol.15, No. 6.

Fundamentals of Remote Sensing: CCRS Remote Sensing Tutorial

Gallo K.P., J.D. Tarpley, A.L. McNab and T.R. Karl. 1995. Assessment of Urban Heat Island: a Satellite Perspective. Atmospheric Research, Vol. 37, pp. 37-43.

Gallo, K.P., A.L. McNab, T.R. Karl, J.F. Brown, J.J. Hood and J.D. Tarpley. 1993. The use of a vegetation index for assessment of the urban heat island effect. International Journal of Remote Sensing, Vol.14, no.11, pp. 2223-2230.

Geist, H.J, and E.F. Lambin. 2001. What Drives Tropical Deforestation? LUCC Project Report Series No. 4, Louvain-la-Neuve, Belgium.

Geoghegan, J., L. Pritchard, Y. Ogneva-Himmelberger, R.R. Chowdhury, S. Sanderson, and B.L. Turner. 1998. Socializing the Pixel and Pixelizing the Social in Land-Use and Land-Cover-Change. In: People and Pixels, D. Liverman, E. Moran, R. Rindfuss, and P. Stern (eds.). Washington, DC: National Academy Press.

Gibson, C., E. Ostrom, and T.K. Ahn. 2000. The concept of scale and the human dimensions of global change: a survey. Ecological Economics. Vol. 32, pp. 217-239.

Gibson, C.C., E. Ostrom, T.K. Ahn. 2000. The concept of scale and the human dimensions of global change: A survey. Ecological Economics. Vol. 32, pp. 217-239.

GIS and Remote Sensing for Archaeology: Burgundy, France

Global Land Cover Characterization

Global Monitoring for Environment and Security

Gridded Population of the World (GPW)

Guide to Current Sensors

Gupta, V. 1994. Remote-sensing and photogrammetry in treaty verification - Present challenges and prospects for the future. Photogrammetric Record. Vol. 14, Iss. 83, pp. 729-45.

Guyer, J. I., and E. F. Lambin. 1993. Land-use in an urban hinterland - Ethnography and remote sensing in the study of African intensification. American Anthropologist. Vol. 95, Iss. 4, pp. 839-59.

Haberl, H. and H. Schandl. 1999. Indicators of sustainable land use: concepts for the analysis of society-nature interrelations and implications for sustainable development. Environmental Management and Health, Vol. 11, No. 3, pp.

Haberl, H., Batterbury, S., and Moran, E. 2001. Using and Shaping the Land: A long-term perspective. Land Use Policy, Vol. 18, Issue 1, pp. 1-8.

Harris, P.M. and S.J. Ventura. 1995. The Integration of Geographic Data with Remotely Sensed Imagery to Improve Classification in an Urban Area. Photogrammetric Engineering and Remote Sensing, vol.61, no.8, pp.993-998.

Hay, S.I., S.E. Randoph, and D.J. Rogers. 2000. Remote Sensing and Geographical Information Systems in Epidemiology. Advances in Parasitology, vol. 47, London: Academic Press, pp. 357.

Hepner, G.F., B. Houshmand, I. Kulikov and N. Bryant. 1998. Investigation of the Integration of AVIRIS and IFSAR for Urban Analysis. Photogrammetric Engineering and Remote Sensing, vol. 64, no.8, pp.813-820.

Hutchison, C. 1998. Social Science and Remote Sensing in Famine Early Warning. In: People and Pixels, D. Liverman, E. Moran, R. Rindfuss, and P. Stern (eds.). Washington, DC: National Academy Press.

Imhoff M.L., W.T. Lawrence, D.C. Stutzer and C.D. Elvidge. 1997. A Technique for Using Composite DMSP/OLS "City Lights" Satellite Data to Map Urban Area. Remote Sensing of the Environment, vol. 61, pp.361-370.

Jasani, B. 2000. Remote monitoring from space: the resolution revolution. The Verification Yearbook 2000, London:

Jensen, J.R. 1996. Introduction to Digital Image Processing, Second Edition. Upper Saddle River, NJ: Prentice Hall.

Jensen, J.R. 2000. Remote Sensing of the Environment: An Earth Resource Perspective. Upper Saddle River, NJ: Prentice

Jensen, J.R. and D.C.Cowen. 1999. Remote Sensing of Urban/Suburban Infrastructure and Socio-Economic Attributes. Photogrammetric Engineering and Remote Sensing, vol.65, no.5, pp.611-622.

Johnson, G. 1930. Peru from the Air. American Geographical Society, New York.

Jones, B. 2001. A Comparison of Visual Observations of Surface Oil with Synthetic Aperture Radar Imagery of the Sea Empress Oil Spill, International Journal of Remote Sensing, Vol. 22, No. 9, pp: 1619-1638.

Karathanassi, V., C.H. Jossifidis and D. Rokos. 2000. A Texture-Based Classification Method for Classifying Built Areas According to their Density. International Journal of Remote Sensing, vol.21, no.9, pp.1807-1823.

Karl, T.R., H. Diaz and G. Kukla. 1988. Urbanization: Its Detection and Effect in the United States Climate Record. Journal of Climate, Vol. 1, pp.1099-1123.

Kelly, C. 1998. Bridging the Gap: Remote sensing and needs assessment - A field experience with displaced populations. Safety Science. Vol. 30, Iss. 1-2, pp. 123-9.

Kristensen, T. K.; Malone, J. B., and McCarroll, J. C. Use of satellite remote sensing and geographic information systems to model the distribution and abundance of snail intermediate hosts in Africa: a preliminary model for Biomphalaria pfeifferi in Ethiopia. Acta Tropica. 2001 Apr 27; 79(1):73-78.

Land Cover Classification System (LCCS)

Landscan 2000

Landscape Epidemiology and RS/GIS

Lawrence, D., D.R. Peart, and M. Leighton. 1998. The impact of shifting cultivation on a rainforest landscape in West Kalimantan: spatial and temporal dynamics. Landscape Ecology, Vol. 13, No. 3, pp. 135-148.

Leddy, R. and Mathur, P. 2002. Estimating Local Populations in West Africa with Lights, Infrastructure, Other. Paper presented at the 2002 ESRI International User's Conference, 8-12 July 2002, San Diego, California.

Liang, S.Y., K.J. Linthicum, and J. C. Gaydos. 2002. Climate Change and the Monitoring of Vector-borne Disease. Medical Student JAMA, Vol 287, pp 2286.

Lightfoot, D. R. 1996. Moroccan khettara: Traditional irrigation and progressive desiccation. Geoforum. Vol. 27, Iss. 2, pp. 261-73.

Lillesand, T., and R. Kiefer. 2000. Remote Sensing and Image Interpretation. New York: John Wiley and Sons, Inc.
Lindsay, S. W. and W. J. M. Martens (1998). "Malaria in the African highlands: past, present and future." Bulletin of the World Health Organization 76(1): 33-45.

Lindsay, S. W. and W. J. M. Martens. 1998. Malaria in the African highlands: past, present and future. Bulletin of the World Health Organization 76(1): 33-45.

Liverman, D., E.F. Moran, R.R. Rindfuss, and P.C. Stern (eds.). 1998. People and Pixels: Linking Remote Sensing and Social Science. Washington, DC: National Academy Press.

Lo, C.P. and B.J. Faber. 1997. Integration of Landsat Thematic Mapper and Census Data for Quality of Life Assessment. Remote Sensing of the Environment, vol.62, pp.143-157.

Lodhi, M. A., F. R. Echavarria, and C. Keithley. 1998. Using remote sensing data to monitor land cover changes near Afghan refugee camps in Northern Pakistan. Geocarto International. Vol. 13, Iss. 1, pp. 33-9.

Longley P.A. and V. Mesev. 2001. Measuring Urban Morphology using Remotely-Sensed Imagery, in Donnay, J-P, M.J. Barnsley and P.A. Longley (eds), Remote Sensing and Urban Analysis. London, England: Taylor & Francis.

Lotze-Campen, H., W. Lucht, C. Jaeger. 2002. A Sustainability Geoscope: defining an integrated information base for nterdisciplinary modeling of global change. Paper presented at the Fifth Annual Conference for Global Economic Analysis, Taipei, June 5-7, 2002.

Lyons, T.R and T.E. Avery. 1977. Remote Sensing: A handbook for Archaeologists and Cultural Resource Managers. Washington, DC: National Park Service.

Madry, S.L.H. and C.L. Crumley. 1990. An application of remote sensing and GIS in a regional archaeological settlement analysis: the Arroux River Valley, Burgundy, France. In: Interpreting Space: GIS and Archaeology, K.M.S. Allen, S.W. Green, and E.B.W. Zubrow (eds). Taylor and Francis, London. pp. 364-381.

Marcolongo, B., and D. M. Bonacossi. 1997. Abandonment of the Qatabanian irrigation system in the Wadi Bayhan Valley (Yemen): A geoarchaeological analysis. Comptes Rendus De L'Academie Des Sciences Serie Ii Fascicule a- Sciences De La Terre Etes Planetes. Vol. 325, Iss. 1, pp. 79-86.

Markowitz, K. 2002. The Legal Challenges and Market Rewards to the Use of Remote Sensing Information as Evidence, Duke Environmental Law & Policy Forum. Vol. 12, No. 1, p. 219.

Marquette, C. 1998. Land Use Patterns Among Small Farmer Settlers in Northeastern Ecuadorian Amazon. Human Ecology, Vol. 26, No. 4, pp. 573-598.

Matson M., E.P. McClain, D. McGinnis and J.Pritchard. 1978. Satellite Detection of Urban Heat Island. Monthly Weather Review, Vol. 106, pp.1725-1734.

Mayhew, S. 1997. A Dictionary of Geography. New York: Oxford University Press.

McCracken, S., E. Brondizio, D. Nelson, E. F. Moran, A. D. Siqueira, and C. Rodriguez-Pedraza. 1999. Remote sensing and GIS at farm property level: Demography and deforestation in the Brazilian Amazon. Photogrammetric Engineering and Remote Sensing. Vol. 65, Iss. 11, pp. 1311-20.

McCracken, S., E. Brondizio, D. Nelson, E. Moran, A. Siqueira, and C. Rodriguez-Pedraza. 1999. Remote Sensing and GIS at Farm Property Level: Demography and Deforestation in the Brazilian Amazon. Photogrammetric Engineering and Remote Sensing. Vol. 65, No. 11, pp. 1311-1320.

MEDEA. 2002. Monitoring Multilateral Environmental Agreements. Report produced by Isciences, L.L.C., under supervision of the MEDEA project.

Mesev, V. 1997. Remote Sensing of Urban Systems: Hierarchical Integration with GIS. Computers, Environment and Urban Systems, vol.21, no.3/4, pp.175-187.

Mertens, B. and E.F. Lambin. 1997. Spatial modelling of deforestation in Southern Cameroon: spatial disaggregation of diverse deforestation processes. Applied Geography, 17: 143-68.

Meyers, M.F., D.J. Rogers, J. Cox, A. Flanhault, and S.I. Hay. 2000. Forecasting disease risk for increased epidemic preparedness in public health. In: Remote Sensing and Geographical Information Systems in Epidemiology, S.I. Hay, S.E. Randolph, and D.J. Rogers (eds.). Advances in Parasitology, Vol. 47, New York: Academic Press.

Millette, T.L., A.R. Tuladhar, R.E. Kasperson, and B.L. Turner. 1995. The use and limits of remote sensing for analysing environmental and social change in the Himalayan Middle Mountains of Nepal. Global Environmental Change, Vol. 5, No. 4, pp. 367-380.

Millington, A., S. Al-Hussein, and R. Dutton. 1999. Population dynamics, socioeconomic change and land colonization in Northern Jordan, with special reference to the Badia Research and Development Project area. Applied Geography. Vol. 19, Iss. 4, pp. 363-84.

Millington, A.C., X.M. Velez-Liendo, and A.V. Bradley. 2002. Scale Dependence in Multitemporal Mapping of Forest Fragmentation in Bolivia: Implication for Explaining Temporal Trends in Landscape Ecology and Applying These to Biodiversity Conservation. Paper presented at the International Society for Remote Sensing of the Environment conference, Buenos Aires, Argentina, 8-12 April 2002.

Moller-Jensen L. 1990. Knowledge-Based Classification of an Urban Area Using Texture and Context Information in Landsat TM Imagery. Photogrammetric Engineering and Remote Sensing, vol. 65, no.6, pp.899-904.

Morain, S.A. 1998. A Brief History of Remote Sensing Applications, with Emphasis on Landsat. In: People and Pixels, D. Liverman, E. Moran, R. Rindfuss, and P. Stern (eds.). Washington, DC: National Academy Press.

Moran, E. and E. Brondizio. 1998. Land -Use Change After Deforestation in Amazonia. In: People and Pixels, D. Liverman, E. Moran, R. Rindfuss, and P. Stern (eds.). Washington, DC: National Academy Press.

Moran, E. F. 1993. Deforestation and land-use in the Brazilian Amazon. Human Ecology. Vol. 21, Iss. 1, pp. 1-21.

Nang Rong Projects

National Remote Sensing and Space Law Center

Nghiem, S., D. Balk, C. Small, U. Deichmann, A. Wannebo, R. Blom, P. Sutton, G. Yetman, R. Chen, E. Rodriguez, B. Houshmand, and G. Neumann. 2001. Global Infrastructure: The Potential of SRTM Data to Break New Ground. White Paper Produced by CIESIN and NASA's Jet Propulsion Laboratory.

Nyerges, A. E., and G. M. Green. 2000. The ethnography of landscape: GIS and remote sensing in the study of forest change in West African Guinea savanna. American Anthropologist. Vol. 102, Iss. 2, pp. 271-89.

Oke, 1973. City Size and the Urban Heat Island. Atmospheric Environment, Vol.7, pp.769-779.

Oke, 1982. The Energetic Basis of the Urban Heat Island. Quarterly Journal of the Royal Meteorological Society, Vol. 108, no.455, pp.1-24.

Olorunfemi, J.F. 1984. Land use and population: A linking model. Photogrammetric Engineering and Remote Sensing, Vol. 50, No. 2, pp. 221-227.

Philip, G., D. Donoghue, A. Beck, N. Galiatsatos. 2002. CORONA satellite photography: an archaeological application from the Middle East. Antiquity. Vol. 76, issue 291, pp.109-118

Pope, K. O., and B. H. Dahlin. 1993. Radar detection and ecology of ancient Maya canal systems: A reply to Adams et al. (1990 (17:2) 241-244). Journal of Field Archaeology. Vol. 20, Iss. 3, pp. 379-83.

Population, Landscape, and Climate Estimates (PLACE)

Pozzi, F. and C. Small. 2001. Exploratory Analysis of Suburban Land Cover and Population Density in the U.S.A. In Proceedings of the IEEE/ISPRS Joint Workshop on Remote Sensing and Data Fusion over Urban Areas, 8-9 November 2001, Rome, Italy, pp. 250-254.

Pozzi, F. and C. Small. 2002. Vegetation and Population Density in Urban and Suburban Areas in the U.S.A. Presented at the Third International Symposyium on Remote Sensing of Urban Areas, Istanbul, Turkey, 11-13 June.

Principles Relating to Remote Sensing of the Earth from Outer Space

Proceedings of the IEEE/ISPRS Joint Workshop on Remote Sensing and Data Fusion over Urban Areas, Rome, Italy, 8-9 November 2001.

Project Gigalopolis

Project Zeugma: The use of remote sensing and GIS for archaeology on the Euphrates

Radeloff, V.C., A.E. Hagen, P.R. Voss, D.R. Field and D.J. Mladenoff. 2000. Exploring the Spatial Relationship between Census and Land-Cover Data. Society and Natural Resources, vol.13, no.6, pp.599-609.

Rao, P.K. 1972. Remote Sensing of Urban "Heat Island" from an Environmental Satellite. Bulletin of American Meteorological Society, vol.53, pp.647-648.

Reining, P. 1979. Challenging desertification in West Africa: insights from Landsat into carrying capacity, cultivation and settlement sites in Upper Volta and Niger. Ohio: Ohio University Press.

Remote Sensing and Environmental Treaties: Building More Effective Linkages

Remote Sensing and Photogrammetry Society: Archaeology Special Interest Group

Remote Sensing Archaeology Research at NASA

Remote Sensing Core Curriculum

Remote Sensing/GIS and Human Health: A Partial Bibliography

Remote Sensing: International Crop Condition and Production Analyses

Rindfuss, R. 2002. Conflicting Demands: Confidentiality Promises and Data Availability. IHDP Update, No. 2, 2002.

Rindfuss, R., and P. Stern. 1998. Linking Remote Sensing and Social Science: The Need and the Challenges. In: People and Pixels, D. Liverman, E. Moran, R. Rindfuss, and P. Stern (eds.). Washington, DC: National Academy Press.

Rindfuss, R., B. Entwisle, S.J. Walsh, P. Prasartkul, Y. Sawangdee, T.W. Crawford, and J. Reade. 2002. Continuous and Discrete: Where they have met in Nang Rong, Thailand. In: Linking People, Place and Policy: A GIScience Approach, S. Walsh and K.Crews-Meyer (eds.). Boston: Kluwer Academic Publishers.

Rindfuss, R.R., S.J. Walsh, V. Mishra, J. Fox, G.P. Dolcemascolo. 2001. Linking Household and Remotely Sensed Data: Methodological and Practical Problems. Prepared for a workshop at the East-West Center, University of Hawaii, November 2001.

Rogers, D.J., S.E. Randolph, R.W. Snow, and S.I. Hay. 2002. Satellite imagery in the study and forecast of malaria. Nature. Vol. 415, 7 Feb 2002, pp. 710-715.

Rosenqvist, A., M. Imhoff, A. Milne, and C. Dobson .1999. Remote Sensing and the Kyoto Protocol: A Review of Available and Future Technology for Monitoring Treaty Compliance, workshop held in Ann Arbor Michigan, USA, October 20-22, 1999. Sponsored by the International Society for Photogrammetry and Remote Sensing and the University of Michigan School of Engineering.

Roth, M., T.R. Oke and W.J. Emery. 1989. Satellite-derived Urban Heat Islands from Three Coastal Cities and the Utilization of Such Data in Urban Climatology. International Journal of Remote Sensing, vol.10, no.11, pp.1699-1720.

Ryznar, R.M., J.D. Nystuen, R.W. Marans, and T.W. Wagner. [undated]. The Greening of Detroit: The Social and Demographic Correlates. Working Paper produced by the University of Michigan Department of Urban and Regional

Satellite Remote Sensing and Archaeology

Schaper, A. 2000. Verifying nuclear arms control and disarmament. The Verification Yearbook 2000, London: VERTIC.

Schweik, C.M., and G.M. Green. 1999. The use of spectral mixture analysis to study human incentives, actions and environmental outcomes. Social Science Computer Review, Vol. 17, No. 1, pp. 40-63.

Seto, E., B. Xu, S. Liang, P. Gong, W. Wu, G. Davis, D. Qui, X. Gu, and R. Spear. 2002. The use of remote sensing for predictive modeling of shistosomiasis in China. Photogrammetric Engineering & Remote Sensing, Vol. 68, No. 2, pp.

Sever, T. L. 1987. Remote-Sensing in Chaco Canyon, Poverty Point, and Costa-Rica. American Journal of Archaeology. Vol. 91, Iss. 2, p. 324.

Sever, T.L. 1998. Validating Prehistoric and Current Social Phenomena upon the Landscape of the Peten, Guatemala. In: People and Pixels, D. Liverman, E. Moran, R. Rindfuss, and P. Stern (eds.). Washington, DC: National Academy Press.

Sheets, P., and T. Sever. 1988. High-tech wizardry. Archaeology. Vol. 41, Iss. 6, pp. 28-35, ill.

Silbernagel, J., S. R. Martin, M. R. Gale, and J. Q. Chen. 1997. Prehistoric, historic, and present settlement patterns related to ecological hierarchy in the Eastern Upper Peninsula of Michigan, USA. Landscape Ecology. Vol. 12, Iss. 4, pp.

Small, C. 2001. Estimation of Vegetation Abundance by Spectral Mixture Analysis. International Journal of Remote Sensing, vol.22, no.7, pp.1305-1334

Small, C. 2002a. High Resolution Spectral Mixture Analysis of Urban Reflectance. Ikonos Special Issue of Remote Sensing of Environment, Submitted 05/2002

Small, C. 2002b. Global Analysis of Urban Reflectance. Presented at the Third International Symposium on Remote Sensing of Urban Areas, Istanbul, Turkey, June 2002.

Socioeconomic Data and Applications Center (SEDAC). 2001. Remote Sensing Applications at the State and Local Level Report of a User Workshop, Lamont-Doherty Earth Observatory Palisades, NY, February 23, 2001.

Southworth, J., and C. Tucker. 2001. The influence of accessibility, local institutions, and socioeconomic factors on forest cover change in the mountains of Western Honduras. Mountain Research and Development, Vol. 21, No. 3, pp. 276-283.

Stefanov W., M. Ramsey and P. Christensen. 2001. Monitoring Urban Land Cover Change: An Expert System Approach to Land Cover Classification of Semiarid to Arid Urban Centers. Remote Sensing of the Environment, Vol. 77, pp.173-185.

Stoffle, R. W., T. W. Wagner, J. J. Luczkovich, and D. B. Halmo. 1994. Reefs from space: Satellite imagery, marine ecology, and ethnography in the Dominican Republic. Human Ecology. Vol. 22 , Iss. 3, pp. 355-78 bibl il map.

Sussman, R. W., L. K. Sussman, and G. M. Green. 1994. Satellite imagery, human ecology, anthropology, and deforestation in Madagascar. Human Ecology. Vol. 22, Iss. 3, pp. 333-54.

Sustainability Geoscope

Sutton, P., and R. Costanza. 2002. Global estimates of market and non-market values derived from nighttime satellite imagery, land cover, and ecosystem service valuation. Ecological Economics, Vol. 41, No. 3, pp. 509-527.

Sutton, P., D. Roberts, C. Elvidge, and H. Meij. 1997. A Comparison of Nightime Satellite Imagery and Population Density for the Continental United States. Photogrammetric Engineering & Remote Sensing, Vol. 63, pp. 1303-1313.

Sutton, P., D. Roberts, C.D. Elvidge and K. Baugh. 2001. Census from Heaven: an Estimate of the Global Human Population Using Night-time Satellite Imagery. International Journal of Remote Sensing, Vol. 22, no.16, pp.3061-3076.

Tappan, G.G., A. Hadj, E.C. Wood, and R.W. Lietzow. 2000. Use of Argon, Corona, and Landsat Imagery to Assess 30 Years of Land Resource Changes in West-Central Senegal. Photogrammetric Engineering and Remote Sensing. June 2000, pp. 727-736.

The Long Term Ecological Research (LTER) Network

The Remote Sensing Tutorial

The Search for Ubar: How remote sensing helped find a lost city.

Thomson, M. C. and S. J. Connor (2001). “The development of malaria early warning systems for Africa.” Trends in Parasitology 17(9): 438-445.

Tucker, C.J., J.M. Wilson, R. Mahoney, A. Anyamba, K. Linthicum, and M.F. Myers. 2002. Climatic and ecological context of the 1994-1996 Ebola outbreaks. Photogrammetric Engineering & Remote Sensing, Vol. 68, No. 2, pp. 147-152.

Turner, M., R. O'Neill, R. Gardner, and B. Milne. 1989. Effects of changing spatial scale on the analysis of landscape pattern. Landscape Ecology, Vol. 3, No. 3/4, pp. 153-162.

UNESCO and New Technologies for Culture

United Nations, 2001. World Urbanization Prospects, 1999 Revision. United Nations.

Urban Forest Research Unit.

Urban Heat Island Program

Urban Remote Sensing

US Global Change Research Program (USGCRP). 2001. Our Changing Planet: The FY 2002 U.S. Global Change Research Program. Committee on the Environment and Natural Resources, Washington, D.C.

USDA Water Conservation Research Laboratory: Remote Sensing Research Program

Veldkamp, A. and Lambin, E. 2001. Predicting Land Use Change. Agriculture, Ecosystems and Environment, Vol. 85, pp.

Vogel, J.M. 2002. Answering the Threat of Global Terrorism, Imaging Notes, Vol. 17, No. 3, May/June 2002.

Vogelamnn, J.E, T. Sohl and S.M. Howard. 1998. Regional Characterization of Land Cover Using Multiple Sources of Data. Photogrammetric Engineering and Remote Sensing, vol.64, no.1, pp.45-57.

Wagner, T.W. and R.M. Ryznar. 1999. Toward Understanding Urban Processes with Remotely Sensed Data: Examples from Detroit. Presented at GeoInformatics99, University of Michigan, Ann Arbor, Michigan, June 19-21 1999.

Walker, R., E. F. Moran, and L. Anselin. 2000. Deforestation and cattle ranching in the Brazilian Amazon: External capital and household processes. World Development. Vol. 28, Iss. 4, pp. 683-99 bibl graph tab.

Walsh S.J., T.P. Evans, W.F. Welsh, B. Entwisle and R.R. Rindfuss. 1999. Scale-dependent Relationship between Population and Environment in Northeastern Thailand. Photogrammetric Engineering and Remote Sensing, vo.65, no.1,

Walsh, S.J., J.P. Messina, K.A. Crews-Meyer, R.E. Bilsborrow, and W.K.Y. Pan. 2002. Characterization and Modeling Patterns of Deforestation and Agricultural Extensification in the Ecuadorian Amazon. In: Linking People, Place and Policy: A GIScience Approach, S. Walsh and K.Crews-Meyer (eds.). Boston: Kluwer Academic Publishers.

Wang, Y. and X. Zhang. 1999. Land Cover Change of Metropolitan Chicago Area from 1972 to 1997 and the Impact to Natural Communities in the Region. Presented at GeoInformatics99, University of Michigan, Ann Arbor, Michigan, June 19-21 1999.

WBGU (German Advisory Council on Global Change). 1996. Annual Report 1996: World in Transition, The Research Challenge. Berlin: Springer Verlag.

Weeks, J. R., M. S. Gadalla, T. Rashed, J. Stanforth, and A. G. Hill. 2000. Spatial variability in fertility in Menoufia, Egypt, assessed through the application of remote-sensing and GIS technologies. Environment and Planning A. Vol. 32, Iss. 4, pp. 695-714.

Weier, J. 2000. Bright Lights, Big City. NASA's Earth Observatory.

Welch, R. 1982. Spatial Resolution Requirements for Urban Studies. International Journal of Remote Sensing, vol. 3, no.2, pp.139-146.

Wilson, D.R. 1982. Air Photo Interpretation for Archaeologists. London: Batsford.

Wood, C., and D. Skole. 1998. Linking Satellite, Census, and Survey Data to Study Deforestation in the Brazilian Amazon. In: People and Pixels, D. Liverman, E. Moran, R. Rindfuss, and P. Stern (eds.). Washington, DC: National

World Commission on Environment and Development (Bruntland Commission). 1987. Our Common Future. Oxford: Oxford University Press.

World Health Organization (WHO). 2001. Malaria Early Warning Systems, Concepts, Indicators and Partners: A framework for for field research in Africa. Roll Back Malaria / Technical Support Network for Prevention and Control of Malaria, Document WHO/CDS/RBM/2001.32.

Xu, H., X. Wang, and G. Xiao. 2000. A remote sensing and GIS integrated study on urbanization with its impact on arable lands: Fuqing City, Fujian Province, China. Land Degradation & Development. Vol. 11, Iss. 4, pp. 301-14.

Yetman, G., I. Mateescu, D. Balk, and U. Deichmann. 2000. A gridded population of the world: The single variable model, presented at the Gridded Population Workshop, 2-3 May 2000, Columbia University, New York, NY.

Yuan, Y., R.M. Smith and W.F. Limp. 1997. Remodeling Census Population with Spatial Information from Landsat TM Imagery. Computers, Environment and Urban Systems, vol.21, no.3/4, pp.245-258.