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Chapter 17

Using Remote Sensing and Geographic Information Systems to Identify the Underlying Properties of Urban Environments

John R. Weeks

Urban places represent built environments that are physically distinguishable from the natural environment, and are thus potentially identifiable through the use of remotely-sensed sources such as satellite images. The urban environment can be defined by classifying images and then combining that information with census data to create a quantitative index of the urban-rural continuum. This is based on the premise that variability in the built environment is associated with variability in human behavior, and that this variability captures the nature of urbanness in human societies. The chapter begins with a justification of the use of the built environment as a signature of urban places. It continues with an overview of how satellite images can be used to distill information about the urban environment, and of the role that geographic information systems (GIS) play in the analysis. It then illustrates this approach to understanding the urbanness of places using data from Egypt. Variables derived from satellite images are combined with census data to improve our understanding of the spatial variability in human behavior in the context of the urban-rural continuum. Finally, ways in which this type of analysis could be used to measure and understand phenomena such as urban sprawl and multinucleation of metropolitan areas are suggested.

The Built Environment as a Signature of Urban Places

Urban places are typically defined by demographers according to criteria of population size and density. To be urban requires that a sufficient quantum of people are living in sufficiently close proximity to one another so that life is demonstrably different from that in rural areas. That difference is often expressed in terms of economic activities. In particular, urban places are routinely defined as concentrations of people who are engaged in nonagricultural activities (Weeks, 2002). Definitions based on size, density, and economic activity all imply a dichotomy between urban and rural, and that notion is almost certainly accurate from an historical perspective. Until only a few hundred years ago, most cities were bounded by protective walls, which offered a clear distinction between the city and the noncity population. In the United States in the 19th and early 20th centuries, rural turned into urban when you reached streets laid out in a grid. Today, such clearly defined transitions are rare. As discussed in the opening essay of this volume, researchers have complained for decades about the arbitrariness of drawing a line between places that are rural on one side and urban on the other.

Over time the distinction between town and country may have become blurred, but in general the distinction illustrates an important point: urban places are identifiable by their infrastructure. As Smailes (1966, p.33) suggested, 'the geographer must regard as urban a particular manmade type of landscape.' Urban places – be they towns, cities, or megalopolises – have, at a minimum, buildings and roads that make them different from the rural countryside. Historically, that difference has always been present, but modern urban places have vastly more complex infrastructure, including electricity lines, gas pipelines, water storage and treatment facilities and water transport pipes, sewers and waste treatment plants, landfills and other refuse facilities, bridges, tunnels, and various aspects of mass transportation and telecommunication.

Yet, many of these aspects of infrastructure, especially the communications-related ones, have now reached into what had previously been thought of as rural places, changing the lives of those residents in the process. This reminds us that important aspects of urbanization are ideational. There is an explicit recognition that urban people order their lives differently from rural people; they perceive the world differently and behave differently. At the same time, living in a rural area in most industrialized societies does not necessarily preclude participation in urban life. The flexibility of the automobile, combined with the power of telecommunications, can put most people in touch with urban life. Even in remote areas of developing countries, radio and satellite-relayed TV broadcasts played on sets powered by a portable generator can make rural villagers knowledgeable about urban life, even if they have never seen it in person (Critchfield, 1994). In the process, people in rural places are becoming more urban, and this serves to change the character of the places where they live.

The increasing connections between the urban and the rural have the effect of urbanizing rural places, helping to explain why the world is on a trajectory toward being predominantly urban: not only are people moving to cities; the cities are moving to people. The direction of movement is important to consider. Rural places tend to be characterized by what they lack – electricity, running water, sewage, paved roads, schools, health clinics and hospitals, diversity of employment opportunities, not to mention the lack of amusements and amenities such as sports teams, theatres, and restaurants. While there are always some people who do not want such things, the evidence suggests that most rural residents prefer to have more, rather than less, of these improvements. For most of human history, a person had to migrate to a city to participate in urban life, but it is now possible for governments to extend many of the characteristics of urban life into rural areas, permanently changing the nature of those places, both ideationally and physically.

As important as ideas are, the signature of an urban place is the built environment, represented most obviously by buildings, roads and sidewalks. A person raised in the city will still be urban even when isolated in the countryside, just as a farmer who moves to the city may never fully adapt to the kind of life demanded by the city. But both people readily recognize the gradations of urbanness or ruralness by the differences in the built environment. Furthermore, differences in the built environment can be shown to be related to differences in the human behavior taking place in those environments. Byrne (2001, p.149) reminds us that, in fact, 'the built environment for urban residents is the locus of the social.' As Winston Churchill once said, 'We shape our buildings, and afterwards our buildings shape us' (Churchill, 1943). This is another way of saying that the context *in* which we live influences *how* we live. Duncan made the classic statement of this:

> A concrete human population exists not in limbo but in an environment. Moreover, to continue to exist, it must cope with the problems posed by an environment which is indifferent to its survival but offering (in varying degree) resources potentially useful for the maintenance of life. By mere occupancy of an environment, as well as by the exploitation of its resources, a human population modifies its environment to a greater or lesser degree, introducing environmental changes additional to those produced by other organisms, geological processes, and the like. Thus, in the language of bioecology, one may say that not only does the environment 'act' upon the population but also the human population 'reacts' upon its environment…The 'adjustment of a population to its environment, therefore, is not a state of being or static equilibrium but a continuing, dynamic process. (Duncan, 1959, pp.681-82).

When Duncan uses the word 'environment', he is referring to the natural environment, in the way that human ecologists have tended to do, but a substitution of 'built environment' for 'environment' keeps the meaning while applying it specifically to human life as organized in cities, towns and villages. The term 'local context', or 'local environment', means the complex of social activities that are taking place within a given built environment.

Social scientists tend to focus on the population and social organizational parts of this system, and spend less time thinking about the environment in which these parts are embedded. In particular, sociologists and demographers tend to be vague, if not dismissive, of the built environment of the buildings, parks, roads, bridges, and the associated infrastructure that humans create out of the natural environment and which become the places where everyday life takes place. Yet, the built environment is, in fact, the actual environment in which a large fraction of humans spend their entire lives. The natural environment is so transformed by urbanization that the majority of urban residents spend little time touching soil and interacting with flora and fauna.

To understand what an urban area is, we can begin with the idea that the local environment of social structures and institutions is the context within which individual lives are understood, and then add to that the notion that the outward manifestation of the social environment is the built environment (the buildings, streets, and infrastructure) created by the people living in those places. This is important both theoretically and methodologically because the social world exists only in our heads, whereas the built environment is the physical representation of the social activities of humans and it may be more measurable than are the attitudes and behaviors of the people themselves. Furthermore, as Bronfenbrenner (1995) notes, individuals and their environments are in constant, reciprocal interplay: there is a dynamic relationship between the built and social environments. Urban places are microcosms of a larger society, shaped by the interaction of demographic processes, social processes, and the built environment in which these processes are being played out. In other words, the urban transition is not just a national pattern that can be laid over a society and understood in those general terms. It is a process that occurs place by place over time, and if we can understand how the demographic and social processes intersect with and interact with the built environment, then we should have a greater understanding of the underlying source of dynamism in urban morphology.

This implies that, if we can quantify aspects of the underlying properties of the built environment, then we can produce an index that measures the degree and/or type of urban place, helping us thereby to move beyond a dichotomy of urban-rural into a genuine continuum of urbanness that encompasses properties of the built environment as well as the behavior (or at least the characteristics of) the people in those environments. Seen in this way, the built environment is not just a proxy for an urban place, but rather it represents an important stage upon which urban life is played out, and different stages demand and/or permit different kinds of human activities. The physical and social worlds are thus highly interconnected. A built environment left unattended by humans slowly reverts to nature, just as a human population living outside a built environment lives within the primitive world of nature, with all of the attendant tasks and risks associated with that life.

I argue that, precisely because the built environment is a signature of urban places, we may be able to use the technology of remotely-sensed imagery and GIS to assist in the development of new approaches to the measurement and quantification of the rural-urban continuum.

Using Remote Sensing to Capture the Urban Scene

Remotely-sensed images range from high-resolution aerial photographs and digital imagery to low-resolution satellite images (which may be either photographs or digital imagery), with most imagery used in social science falling in the middle of that range. Resolution refers to the size of the scene on the ground captured by the smallest pixel (picture element) in the image. Thus, a 1-meter image means that the smallest amount of detail in the image is 1 meter by 1 meter in size on the ground. Images also vary according to the bandwidth of light captured by the sensor (camera or other recording device), ranging from panchromatic (gray scale) to multispectral (visible red, green, blue, and near-infrared bands, as well as other bands that are not visible to the naked eye). A basic premise of remote sensing is that the earth's features and landscapes can be discriminated, categorized, and mapped according to their spectral characteristics. The nuclear reactions of the sun produce electromagnetic energy, and this energy is propagated by electromagnetic radiation at the speed of light through space, reaching the earth's atmosphere practically unchanged. Part of it is absorbed as it passes through the atmosphere, and the remainder continues on to the earth's surface. The part that continues is then either reflected or absorbed by objects on the earth's surface and reradiated as thermal energy. 'Passive' remote-sensing systems operate by measuring the energy which is reradiated or reflected from the object of interest back to the remote sensor. The sensors are most often optical (measuring light reflectance), but they may also be thermal (measuring heat reflection), or something else, depending upon the wavelength of the specific kind of energy that the sensor is designed to measure (Lillesand and Kiefer, 2000).

In order to appreciate the value of remotely-sensed images for demographic analysis, it is crucial to understand exactly what it is that can be extracted from an optical satellite image. The image itself is composed of a mosaic of individual pixels representing information that has been captured for an area on the ground that is equal to the resolution of the image. The information recorded for each image depends upon the particular sensor. For a panchromatic image, information is recorded for only one band of reflectance, based on the brightness of the pixel in the visible range of wavelengths between approximately 0.4 and 0.7 micrometers (µm). We typically call this a black-and-white image, although really it is mainly shades of gray, with black and white representing the two extremes. Technically, it is brightness at the satellite that is recorded, but through a series of adjusting techniques, we are able to estimate what the brightness is on the ground at that place shown on the image. For a multispectral image, information is recorded for two or more bands of reflectance. The Indian Remote Sensing multispectral image (IRS-IC LISS-III) which is used in the research reported here records three bands in the visible and near infrared (VNIR) range, including green (0.520-0.590 µm), red (0.620-0.690 µm), and near infrared (0.770-0.860 µm) at 24-meter spatial resolution, and one band in short wave infrared (SWIR – 1.50-1.70 µm) at 71-meter spatial resolution.

For work at the equivalent of the census-tract level of analysis, the ideal image is a relatively high-resolution multispectral image. In the research that is discussed here, only commercially available satellite images are employed. The 'highest-end' commercial options include 1-meter resolution IKONOS panchromatic images and 4-meter IKONOS multispectral images, which can be merged with the 1-meter pan image to create representative 1-meter color imagery. There is currently no archive of these images for the study site in Egypt, and so they would have to be specially ordered at considerable cost. Existing archived images for the late 1990s and early 2000s include Landsat (US) Thematic Mapper 30-meter multispectral images, SPOT (French) 20-meter multispectral images, IRS (Indian Remote Sensing) 5-meter panchromatic images and 24-meter multispectral images, and SPIN-2 (Russian) 2-meter panchromatic images.

Analysis of Images for Urban Areas

Images were first derived from aerial photography in 1858, and they have been useful in the analysis of urban areas for several decades. The Australian Bureau of Statistics notes that an urban center with a population between 1,000 and 19,999 is to be delimited 'subjectively by the inspection of aerial photographs, by field inspection and/or by consideration of any other information that is available' (Australian Bureau of Statistics, 2001). In the 1960s, Noin (1970) derived estimates of the rural population of Morocco by examining aerial photographs to determine the number of housing units in rural areas and then applying a household-size multiplier to dwellings to estimate the population. One of the more sophisticated applications of aerial photography was that by Green (1955), who developed a method to analyze the social structure of urban areas based on a set of surrogates obtained from the aerial photos. Using black-and-white photos, he created social indices based on characteristics such as neighborhood location, single-family homes, and density of housing. In most applications of aerial photography, however, information is obtained from an image captured on film by means of *interpretation* of the image by humans. This requires a great deal of training and practice and it is not necessarily replicable from place to place and time to time. When images are captured digitally, it is possible not only to interpret them, but also to *classify* the information using a mathematically-derived algorithm that is replicable and which can produce a statistically quantifiable result.

The classification of digital images has represented a breakthrough for analyzing the earth's surface because the process can be automated on the computer and repeated for images representing different times and places. Image classification is the process whereby all pixels in the image are categorized into a land-cover class or theme (Lillesand and Kiefer, 2000). As we (or, more accurately, computers using an algorithm that we have developed) look at each pixel, the question is: Does this pixel represent vegetation (and perhaps a specific type of vegetation), or bare soil, water, shade, or an impervious surface (such as asphalt or cement)? These are the basic building blocks of the natural and built environment and each type of land cover is associated with a particular 'spectral signature,' which represents a combination of wavelength values shared by one class of surface (such as vegetation), but not by the others. The higher the resolution (i.e. the smaller the pixel size), the more accurately we are able to classify a pixel because it is more likely that the pixel will include only one type of land cover. On the other hand, for lower-resolution images, the more likely it is that the pixel will represent a mixture of different land covers, forcing us to make decisions about how appropriately to classify the image. Once we have classified the image according to land cover (the physical property as seen from the air), we are in a position to use information from other sources to make inferences about the way in which the land is being used (which is a socially derived category). From this process we are able to create variables describing the environmental context of a specific place.

The panchromatic image is not capable of classification into land-cover types, but it can be used to derive information about brightness and about the texture at the earth’s surface. The variability from one pixel to another in the amount of brightness (the gray scale) at night, for example, can be used as an index of economic wellbeing. In a rural village light at night may indicate electrification, indicating a higher level of economic development than a similarly situated village emitting less light. Weeks (2003) used the brightness of night-time lights to assess the relationship between lighting and crime in an urban center in California. Light reflected from the surface during the day is more varied, of course, than at night and this provides a way of measuring texture at the earth’s surface. Very little variability from pixel to pixel in the amount of brightness would indicate a homogeneous surface, and a great deal of variability would indicate a heterogeneous surface. In a city such as Cairo, Egypt, the older parts of the city, characterized by low-rise buildings and narrow streets – what Rodenbeck (1999, p.224) has called the ‘higgledy-piggledy burrows’ of Cairo’s popular quarters – will exhibit a relatively homogeneous texture, whereas newer ‘irregular’ suburbs may be expected to exhibit considerable heterogeneity in texture. By combining the land-cover classification with the texture classification, we are in a position to describe the physical nature of the urban scene captured by the remote-sensing device.

In general, vegetation is easier to classify than are humanbuilt structures, and so the classification of remotely-sensed urban imagery is much more cutting-edge than is the classification of rural areas (Jensen and Cowen, 1999). Most of the literature on the classification of remotely-sensed images has emphasized the creation of variables describing the natural environment of plants, soil, and water. Urban environments include a complex mix of buildings, streets and other infrastructure, as well as vegetation, soil, and water, often interwoven with one another. Methods for dealing with urban images are still evolving, but at an increasingly rapid pace (Gruen *et al*., 1995; Cowen and Jensen, 1998; Rindfuss and Stern, 1998; Jensen and Cowen, 1999). Seeking social meaning in imagery holds the promise of providing information that speaks to the core research issues of the social sciences (Geoghegan *et al.*, 1998). The interface between remote sensing and social science depends on the kind of features that can be detected such as landuse/landcover, buildings, infrastructures, roads network, and also on how often and to what detail such data can be obtained (i.e. spatial and temporal resolution).

Numerous studies have documented the ability to extract population information either directly from remotely-sensed data, or indirectly by analyzing information derived from the imagery (Lo, 1995; Elvidge *et al.,* 1997; Lo *et al*., 1997; Mesev, 1998; Ryznar, 1998; Tanaka *et al.,* 1999; Weeks *et al.,* 2000; Rashed *et al.,* 2001). Lo (1995) was able to derive population estimates from remote imagery by testing a number of regression models that link spectral radiance obtained from a multispectral SPOT image with high and low population densities in some metropolitan areas in Hong Kong. Elvidge et al. (1997) and Doll *et al.* (2000) have used satellite images to identify the relation between population, gross domestic product and electric power consumption in 21 countries. They concluded that VNIR (visible and near infrared) emissions of nighttime lights could be successfully used to define and update the spatial distribution of human populations, particularly in urban areas. Other studies have shown that community-level demographic characteristics such as income and education are strongly correlated with variables extracted from high-resolution remote imagery (Jensen and Cowen, 1999). Examples of such variables extracted include building sizes and densities, parking lots, existence of water tables, street widths, and health of landscaping.

These studies have demonstrated the potential value of remotely-sensed images, but we are just now in the process of developing algorithms for the automatic extraction of information from images in ways that allow us to use these data in a quantitative spatial analysis of the urban scene over a fairly large area.

Using GIS to Analyze the Urban Scene

Although we may have successfully classified the pixels in the image according to land-cover type and texture, the analysis of that information requires that we link the location of each pixel to other information about what is happening on the ground at that location. For the purpose of analyzing the urban structure, we are particularly interested in joining the data from the remotely-sensed image to information gathered at the local level in the census, such as the equivalent of the US census tract. We accomplish this in a GIS environment, which allows us to match data from one layer (such as the image analysis) for a specific geographic area (such as a census tract) with data from another layer (such as the census data) for that same geographic area. It is not an exaggeration to say that the remotely-sensed data would be useless to us unless they were incorporated into a GIS.

A GIS is a computer-based system that allows us to combine maps with data that refer to particular places on those maps and then to analyze those data and display the results as thematic maps or in some other graphic format. The computer allows us to transform a map into a set of areas (such as a county or a state or a census tract), lines (such as streets or highways or rivers), and points (such as a house or a school or a health clinic). Our demographic data must then be georeferenced (associated with some geographic identification such as an address, ZIP code, census tract, county, state, or country) so that the computer will link them to the correct area, line, or point. If the computer knows that a particular set of latitude and longitude coordinates represents the map of Egypt, then our data for Egypt must be 'georeferenced' to that particular location. Or, if we have a survey of households, then each variable for the household would be georeferenced to the specific address (the point) of that household.

The 'revolutionary' aspect of GIS is that the georeferencing of data to places on the map means that we can combine different types of data (such as census and remotely-sensed data) for the same place, and we can do it for more than one time (such as data for the 1986 and 1996 censuses of Egypt and imagery for those two dates). This greatly increases our ability to visualize and analyze the kinds of demographic changes that are taking place over time and space. Since the census data will be aggregated at a specific geographic scale, with variables such as proportion of adult women who are literate, the data from the image must also be aggregated up to that same level of geography. Thus, we must create summary indices of land-cover types and texture information that match the geography of the census data. It is easiest to explain this process through an illustration.

An Illustration from Greater Cairo and Menoufia, Egypt

The urban area of Greater Cairo comprises the governorate of Cairo on the east side of the Nile River as it travels through the metropolitan region, together with the portion of the governorate of Giza that is along the west bank of the Nile River within the metropolitan region, plus the southern tip of the governorate of Qalyubia – which currently represents the northernmost reach of Greater Cairo. The area's location is shown in Figure 17.1. Nearly one in five Egyptians lives in the Greater Cairo region and for centuries it has been a quintessentially primate city, dominating the social, economic, and political life of the region. Its location is a geographically strategic crossroads (Palmer-Moloney, 2001). 'When you see Cairo in its full setting, the whole city suddenly makes sense. Look south and you can see the long flat river coming out of Africa; look west and you can see the first veins of the rich Delta; look north and the river is heading determinedly for the Mediterranean and for Europe .…Cairo itself is built at the meeting place of Africa, Egypt, Europe, Arabia, and Asia' (Aldridge, 1969, p.5). The United Nations Population Division (UN, 2003) lists the population of Cairo to be 9.5 million as of 2000 (the 20th most populous city in the world), with a projected population of 11.5 million in 2015 (when it would be the 18th most populous).

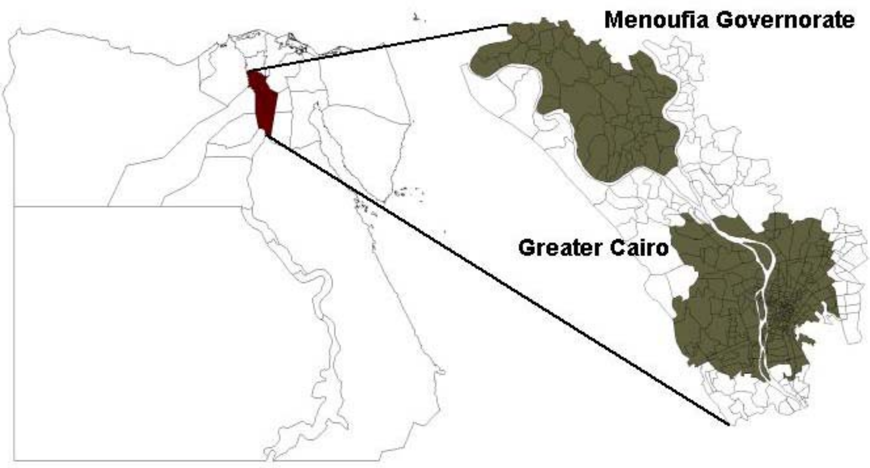

Figure 17.1 Greater Cairo and the governorate of Menoufia in context

Menoufia is a predominantly rural governorate (the equivalent of a state in the US or a county in the UK), just to the northwest of Greater Cairo. By government definitions of urban (which are based on administrative criteria), 80 per cent of Menoufia's population of about 3 million people resides in rural places. We have satellite imagery of Cairo and Menoufia acquired for 1996 (multispectral) and 1998 (panchromatic) and the census tract ('shiakha', literally the area controlled by a sheikh) boundaries from the 1996 census. Our goal is to combine data extracted from the image for each shiakha with data from the 1996 census for that area, in order to test the idea that data from the images will improve our ability to quantify the nature of human settlements.

Extracting Variables from Remotely-Sensed Imagery

As discussed above, there are two different types of variables that can be obtained from the image: (1) land-cover classification; and (2) texture. If the resolution of the image is sufficiently high (e.g. 1m or less), it may be that each pixel will represent only one type of land cover, and so we can make an accurate 'hard' classification. However, for lower-resolution images – the kind that are more readily available for different places and for different times – each pixel is likely to represent a mix of different land-cover types. As a result, a hard classification will probably represent only a part of the pixel and will inaccurately describe the remainder of the area covered by that pixel. A variety of techniques, including maximum likelihood classifiers, have been employed to try to increase the accuracy of the overall (or 'hard') classification of each pixel (see, for example, Curran *et al.,* 2000; Mesev *et al*., 2001).

Our approach to classifying the urban scene is to employ a 'soft' approach, called spectral mixture analysis (SMA). Since our multispectral image has a resolution of 24 meters, we know that the probability is very low that any single land-cover classification will accurately represent a particular pixel. In the 'soft classification' approach, each pixel is assigned a class membership probability for each land-cover type. Fuzzy classification and SMA are two families of techniques designed to provide a 'soft' classification of mixed pixels. The basic difference between them is that SMA is based on a physical model of the mixture of discrete spectral response patterns (Roberts *et al.,* 1998), thus providing a deterministic method for addressing the spectral mixing problem rather than a statistical method as in the case of the fuzzy approach (Mather, 1999). SMA allows us to decompose each pixel into the percentage of the pixel that is represented by the major land-cover classifications that can be derived from the image. In this way, we create a profile for each pixel of its constituent parts, and by aggregating those values over the entire shiakha, we are able to define the land cover of the shiakha in terms of the percentage of the earth's surface that is covered by particular types of cover. We have thus far favored the use of SMA over fuzzy-classification techniques, because it serves our purpose of deriving standardized and comparable RS measures that can be utilized with census data in a GIS to study demographic dynamics in urban areas.

SMA was developed initially for use in classifying the natural environment, but we have shown that it also makes sense for urban environments. The details of the procedure are found elsewhere (Rashed *et al.*, 2001), but here it is worthwhile discussing some of the underlying assumptions. Spectral mixing occurs when the spectrum measured by a sensor is a mixture of the spectral response of more than one component within the scene (Adams *et al*., 1993). That is, various materials with different spectral properties are represented by a single pixel on an image. A spectral mixture model is a physically-based model in which a mixed spectrum is modeled as a combination of 'pure' spectra, called *endmembers* (Adams *et al*., 1993; Roberts *et al.,* 1998). Linear SMA is the process of solving for endmember fractions, assuming that the spectrum in each pixel on the image represents a linear combination of endmember spectra that corresponds to the physical mixture of some components on the surface, weighted by surface abundance (Tompkins *et al.,* 1997).

The conceptual model selected to extract image endmembers from the RS data is Ridd's VIS model (Ridd, 1995). The VIS model represents the composition of an urban environment as a linear combination of three types of land cover, namely green Vegetation, Impervious surfaces, and bare Soil. Just as soils may be described in terms of their proportions of salt, silt, and clay using the traditional triangular diagram, so various subdivisions of urban areas may be described in terms of proportions of vegetation, soil, and impervious surface. Ridd's VIS model offers an intuitively appealing link to the spectral-mixing problem, because the spectral contribution of its three main components can be resolved at the subpixel level using the SMA technique. The model was originally applied to American cities, but it has also been tested with data from Australia (Ward *et al*., 2000) and Thailand (Madhavan *et al.,* 2001). The results show that the model is robust outside the United States, although the model may require an additional component (e.g. water/shade) to achieve an accurate characterization of the morphology of non-US cities.

Successful SMA application relies on the accuracy of endmember selection. If the endmembers are incorrect in the physical sense, then the fractional abundances are also incorrect and the results of SMA become meaningless. The selection of endmembers can generally be done in two ways, either by deriving them directly from the image (referred to as *image endmembers),* or from field or laboratory spectra of known materials (referred to as *reference endmembers).* Since we do not have reference endmembers collected from the study sites, we use image endmembers in the SMA stage. Several methods of identifying image endmembers have been described in the literature (Milton, 1999). The approach we have adopted to select image endmembers is a compromise between manual and automated ('Purity Pixel Index') approaches (see Boardman, Kruse, and Green, 1995).

The result, then, is a set of endmember fractions representing the percentage of each of four different types of land cover, classified from the modified VIS model as vegetation, impervious surface, bare soil, and our addition to the model of water and/or shade. Texture transform analyses are then used to add additional information to the classification results, to quantify the degree of variability in the image from one pixel to the next. After classifying the imagery data and obtaining quantifiable indicators of variations in the physical environment, they are linked to census-derived variables within the GIS environment. To do so, the several classes, as well as the texture bands, are converted into raster grids such that each class is represented by a single grid. The next step is to convert each grid into a polygon coverage, with each pixel being converted into a polygon with an area matching that of the remotely-sensed image's resolution (in this case 24 square meters). Resultant coverages are then clipped to the outside borders of the study area. Next, a coverage of the shiakhas is laid over each class's coverage and a unique code is assigned to each pixel (represented by a polygon) according to which census tract (shiakha or locality) it was located within. For each class coverage, the area of all pixels belonging to the same census tract is summed, and the total area is then normalized by calculating the ratio of the resultant area to the census tract's area. The end product is a normalized value (ranging from 0 to 100) for each of the classes assigned to each census tract, indicating the percentage of pixels in that census tract that are classified into this particular class. Each class represents a different aspect of the urban environment (such as areas dominated by tall buildings, areas dominated by low-rise buildings, areas with vegetation, areas with water or shade, areas that are highly variable in texture, and areas that are homogenous with respect to texture). These classes thus represent the variables derived from the images, and the percentage of pixels in each class is the measurement of that variable within that geographic area.

Predicting an Urban Gradient from the Remotely-Sensed Image

The quantification of human settlements in terms of their degree of urbanness should permit us to move from thinking in terms of a rural-urban dichotomy to the notion of an urban gradient. This builds on the concepts inherent in Christaller's (1966) central-place theory, but with the modification that, while most theories of urbanization take each city as the unit of analysis, our approach is to look at each city as a dynamic region undergoing constant change with respect to its urban characteristics. In the gradient conceptualization, we would expect that the geographic center of a city would be most urban, and that urbanness would decline with distance from the center. Over time, of course, we would expect to find that diffusion of urbanness, and various processes such as counterurbanization (Champion, 1989), would contribute to an increase in the urban characteristics at increasing distances from the center. Indeed, this might lead to mutations into multiple nuclei as some areas away from the center take on the characteristics that at an earlier time were solely the properties of the center.

Population density and nonagricultural activities are the most often used indices of an urban place, and have been used as the initial measures of an urban gradient in Cairo and Menoufia, with the task then of evaluating how well they are predicted solely on the basis of the information derived from the remotely-sensed images. In other words, how closely associated are the usual definitions of urban places with the characterization of the environment context that includes information obtained from a satellite image?

We have data for 300 shiakha in Greater Cairo, and an additional 314 shiahka in the neighboring rural governorate of Menoufia. Population density in Cairo ranges from a low of 618 person per square kilometer (in an area on the edge of the Mukatim desert to the southeast of downtown Cairo) to a high of 359,000 (in the parts of south central Cairo dominated by high rise apartment buildings), with a mean for the city of 45,000. The distribution is highly skewed, with the highest densities being found in a relatively few neighborhoods and with most neighborhoods having more moderate levels of density. Density is generally lowest in the outer ring of Cairo, but there are some clearly defined spatial patterns that can be seen in Figure 17.2, which maps population density in Greater Cairo and Menoufia.

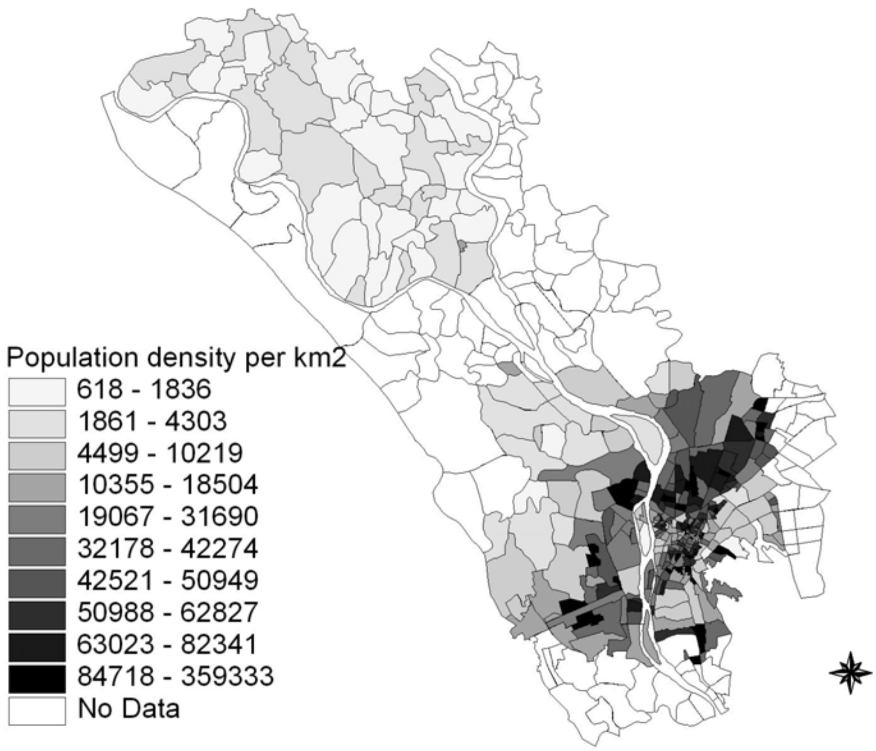

Figure 17.2. The urban gradient in Cairo and Menoufia measured by population density

In Menoufia the highest density is 14,138 per square kilometer, with a low of 145 and an average density of 1,851. That density definition includes the entire area of each shiakha. If we look only at the built area of each shiakha, we find that the rural villagers are actually living much more densely. The built area of the average village comprises 10 per cent of the land area of the shiakha. If we assume that all people in the shiakha reside within the boundaries of observable built area, then the average population density in Menoufia is just under 45,000 persons per square kilometer, almost exactly the same as in the Greater Cairo area. However, to be consistent with the general principle of defining density as population per total area, I have used the standard definition of population density in this analysis.

Economic activity was measured in terms of the percentage of economically active males aged 15 and older who were employed in any sector other than farming, fishing, hunting, or mining. Within Greater Cairo, this ranged from a high of 100 per cent (largely in the center of the city) to a low of 41 per cent in the northernmost shiakha, which is actually in the governorate of Qalyubia, with an average of 97 per cent of each shiakha's labor force being employed outside of agriculture. Even in Menoufia, despite its characterization as a rural governorate, the average village had 65 per cent of males employed outside of agriculture, with a range from a high of 94 per cent in a northeastern shiakha to a low of 29 per cent in the southern tip of the governorate. The bivariate relationship between these two traditional measures of urbanness is only 0.580, indicating an interaction between the two variables, but also some relative independence: they are not measuring exactly the same phenomena. However, the spatial pattern is very similar for the two variables with the exception that density varies quite a bit in the center of Cairo, whereas the percentage of males employed outside of agriculture does not.

A combined index was created by averaging the z-scores calculated for each of the two variables. This implicitly weights each variable equally and additively. The spatial distribution of this variable is shown in three dimensions in Figure 17.3. The general pattern is for the center of the city to be more 'urban' with the index of urbanness dropping off especially in the northwestern direction, and to be low in Menoufia.

Now the question is whether these measures of urbanness within Greater Cairo and Menoufia can be predicted by variables extracted from the remotely-sensed image. We have five predictor variables from the image: (1) the percentage of an area that is classified as vegetated (VEG); (2) the percentage of an area that is classified as representing soil or materials (such as bricks) made from local soil (SOIL); (3) the percentage classified as impervious surfaces (such as concrete or asphalt roofs or roads) (IMP); (4) the percentage classified as water or shade (which will largely be derived from the shadows of buildings) (SHD); and (5) a texture measure that indexes contrast from one pixel to another (CON).

Table 17.1 shows the results of the bivariate correlation coefficients between each of these variables. Overall it can be seen that the correlations are quite high between each of the measures from the satellite imagery and both of the urban definition variables. The contrasting-texture variable emerges as the single best predictor of both population density and the percentage of males in nonagricultural activities, but the soil and vegetation variables are close behind. The closeness of fit of all of these variables suggests two things: (1) the remotely-sensed data can provide a good proxy for the census-based variables; and (2) by combining the variables we may be in a position to better model the urban-rural continuum.

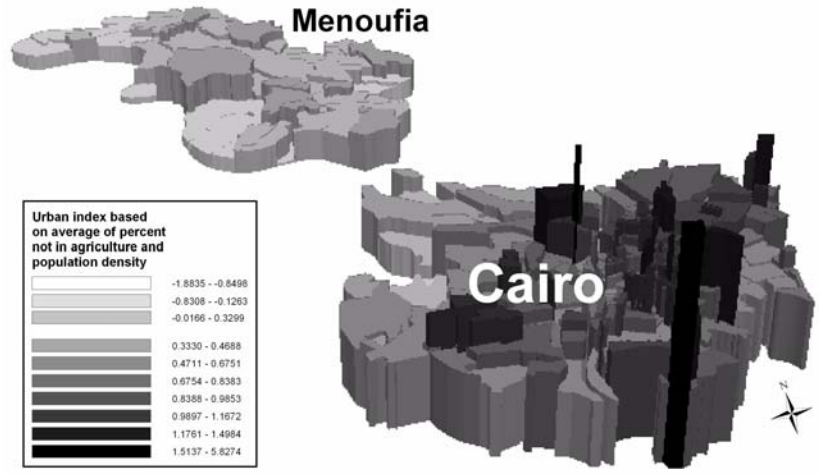

Figure 17.3 The urban gradient in Cairo and Menoufia measured by a variable combining population density and proportion of males not in agriculture

Table 17.1 Bivariate correlation coefficients between census-based measures of urban-rural and the variables derived from the remotely-sensed imagery

	Population per sq km	% males not in agriculture	Contrast in texture (CON)	Vegetation (VEG)	Shade/water (SHD)	Impervious surface (IMP)	Soil (SOIL)
Population per sq km	---	0.580	-0.617	-0.613	-0.472	0.614	0.578
% males not in agric		---	-0.827	-0.803	-0.596	0.699	0.834
CON			---	0.786	0.670	-0.702	-0.881
VEG				---	0.530	-0.739	-0.835
SHD					---	-0.754	-0.678
IMP						---	0.781
SOIL							---

The ability of the remotely-sensed data to predict the census-based variables was tested through step-wise ordinary least-squares regression, and the results are shown in Table 17.2. With population density as the dependent variable, four of the five variables from the image emerge as statistically significant predictors of population density. The most important of these, as measured by the standardized beta coefficient, is the amount of contrasting texture (variability at the earth's surface). Texture is negatively associated with density, reflecting the greater variability of the surface in those places where density is low. Table 17.2 shows that the higher the fraction of impervious surface, the higher the population density, as one might expect. Also in the expected direction are the associations of more vegetation and more soil with lower densities. Overall, these variables combine to explain 46 per cent of the variation from shiakha to shiakha in Greater Cairo and Menoufia governorate with respect to population density. The z-normalized Moran's I is calculated as a measure of spatial autocorrelation in the residuals, and the value of 1.50 suggests that there is not a statistically significant amount of spatial autocorrelation.

Table 17.2 Predicting census-based urban indices from the remotely-sensed images

Predictor variable	Dependent variable: Population density		Dependent variable: % males not in agriculture		Dependent variable: Z-normalized average of density and % males not in agriculture	
	Beta	Significance	Beta	Significance	Beta	Significance
VEG	-0.273	0.000	-0.292	0.000	-0.312	0.000
SOIL	-0.268	0.001	0.283	0.000		ns
IMP	0.344	0.000		ns	0.212	0.000
SHD		ns		ns		ns
CON	-0.392	0.000	-0.348	0.000	-0.415	0.000
Adjusted R^2	0.463		0.757		0.742	
Moran's I (z-normal)	1.50		1.14		1.42	

See Table 17.1 for key to predictor variables. Blank cells indicate that the beta coefficients were not statistically significant at or beyond p=.05.

Using the proportion of the male labor force in nonagricultural jobs leads to slightly better results (Table 17.2, middle columns). Once again, the contrasting texture is negatively associated with nonagricultural economic activity and, not surprisingly, the percentage of an area classified as vegetated is strongly and negatively predictive of this aspect of being an urban place. The percentage classified as soil is positively associated, probably indicating that more builtup areas, even when made of brick, are less likely to be associated with agricultural occupations. Overall, these variables combine to explain 76 per cent of the variability in the nonagricultural percentage, and Moran's I once again indicates that there is no statistically significant pattern of spatial autocorrelation in the residuals.

The index that combines population density and the proportion of the labor force in nonagricultural jobs (Table 17.2, right-hand columns) also picks up the most significant predictor variable from each of those two dependent variables. Thus, for the combined index, the most important predictor among the remotely-sensed image variables is the contrasting texture, followed by the amount of vegetation, which is negatively associated with urbanness. The other statistically significant predictor variable is the amount of impervious surface, which is positively associated. The other variables drop out of the model. Overall, these three variables extracted from the remotely-sensed image combine to explain 74 per cent of the variation in this combined density/nonagricultural index.

Using the Remotely-Sensed Variables to Create an Index of Urbanness

Given the high correlations between the usual indices of urban and the data extracted from the remotely-sensed image, I have created an index of urbanness that represents the combination of data from the remotely-sensed image and the more traditional measures of urban place. Principal components analysis (PCA) was used to combine the five variables derived from the remotely-sensed images with population density and the proportion of the male labor force engaged in other than agriculture. The PCA provides a convenient way to weight each of the variables and combines them using the statistically-derived component score coefficients. All seven variables loaded into one component, with nearly equal component score coefficients. In essence, the resulting index amounts to having added up the z-scores for each variable, in much the same way as for the index that combined only population density and the proportion of the male labor force engaged in nonagricultural activity.

This composite index was normalized so that the lowest score was zero and the highest score was 1. This produced a mean of 0.35 with a standard deviation of 0.24. Because of the high intercorrelation among variables, the spatial distribution of urbanness is similar to that which was generated by other measures, as can be seen in Figure 17.4, in which a three-dimensional map is used so as to better visualize the urban gradient. That map shows a gradient of urbanness from the center, particularly on the east side of the Nile (the older part of Cairo) spreading out especially to the newer urban areas on the west side of the Nile (in Giza governorate) and as Cairo stretches into the farmland of the delta, with less urbanization in Menoufia. Nonetheless, there is variability in urbanness, even in predominantly rural areas.

It was hypothesized that these differences in urban characteristics, representing aspects of both the built and social environments, would be associated with differences in the demographic characteristics of places. Although we do not have a great deal of detailed data with which to test this, Table 17.3 shows the average values for three different types of population characteristics drawn from the 1996 census of population, for each of ten decile categories of the urban-gradient index, where 1 indicates the lowest level of urbanness among the 614 shiahka in Greater Cairo and Menoufia and 10 represents the highest level. The table also shows the average values for each variable that is a component of the urban-gradient index.

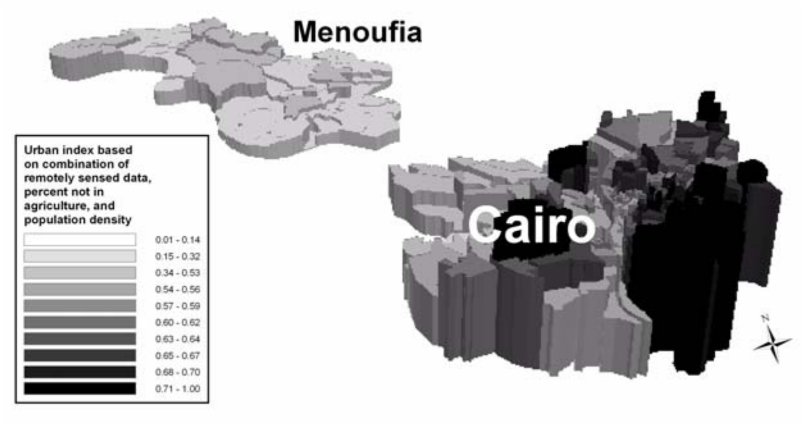

Figure 17.4 Urban-gradient index combining population density, proportion of males not in agriculture and remotely-sensed variables

Table 17.3 Three demographic characteristics and urban-gradient index variables for areas of Greater Cairo and Menoufia, according to level on the urban-gradient index

Urban gradient in deciles	% population aged under 15	% women 15+ never married	% women 15+ with more than primary education	Variables in the urban-gradient index						
				% males not in agriculture	Population per sq km	CON	VEG	SHD	IMP	SOIL
Least urban										
1	37.6	21.7	28.5	55.9	1,375	194.8	30.7	41.1	28.2	2.2
2	37.4	22.2	28.7	61.6	1,700	195.2	27.3	40.1	31.9	2.3
3	36.9	21.8	31.9	65.3	1,531	194.5	25.9	39.2	34.3	2.4
4	37.5	22.1	31.8	66.3	1,771	192.1	23.8	38.8	37.6	1.9
5	37.1	21.8	34.9	73.3	2,067	190.6	22.1	37.1	39.7	2.3
6	31.9	21.9	41.7	89.0	12,266	105.8	16.6	31.9	45.1	12.1
7	23.2	27.5	52.0	98.7	35,139	58.9	2.9	29.2	50.3	20.7
8	23.2	28.2	52.1	99.0	43,782	54.5	1.7	25.8	54.6	22.0
9	26.8	27.5	49.5	99.0	51,632	54.7	1.2	21.0	59.9	22.7
10	28.6	25.6	43.1	99.0	79,990	58.0	0.9	15.4	68.5	25.6
Most urban										

See Table 17.1 for key to remotely-sensed variables.

These data show that the percentage of the population that is under 15 years old is considerably higher in the lower few deciles, and then drops after the fifth decile is reached. Conversely, the percentage of women aged 15 and older who are never married (a proxy for age at marriage) is lowest in the least urban deciles and then rises beginning in the seventh decile. There is a more striking trend with respect to the education of women. In the lowest decile of urbanness only 28 per cent of women aged 15 and older have more than a primary level of education, whereas that nearly doubles to 52 per cent by the seventh decile. It can be noted that the most urban decile (10) is not the one with the most urban demographic characteristics in terms of age structure, marriage patterns, and educational levels. This is partly a scale problem, and partly a problem with the influence of population density on the index of urbanness.

The scale issue relates to the fact that, as can be seen especially in Figure 17.2, the shiakha in our data set are not of uniform size. In particular, the shiakhas in the older part of Cairo are considerably smaller in area than those in the suburbs. As a consequence, these smaller geographic areas can be more influenced by one or two large high-rise apartment buildings. In Cairo, as in many cities of developing countries, these high-rise blocks tend to house younger couples with their children, thus raising the population density (a decidedly urban characteristic) without all of the other attendant urban characteristics being present. Indeed, the central part of Cairo, near Tahrir Square, would be thought of by most people as the most urban part of the city, but its density is lower than in those newer areas with high-rise apartments, and it has more vegetation and more textural variability than the newer concrete blocks of apartments.

These data are suggestive of the idea that, even within the boundaries of a large city, an index of urbanness allows us to distinguish among differences in social behavior, and even to rethink what ‘urban’ means. The less urban portions of Cairo are characterized by demographic features associated with more traditional attitudes toward women and families – less value placed on education of women, and more value placed on younger age at marriage and family-building activity – but so are the most urban places, with the more traditionally urban places between those extremes. This sort of variability is instructive because it forces us to recognize the spatial variability that exists within an area that is normally thought of as monotonically urban.

Discussion and Conclusion

Our interest is in developing an urban-gradient index for all inhabited areas (excluding wilderness and desert regions), and we have taken some preliminary steps to do this in Egypt, using data for Greater Cairo along with data for the largely rural governorate of Menoufia. Agricultural areas are usually defined almost automatically as rural because of the low population densities that are obviously associated with places in which a large fraction of the land is devoted to growing crops. However, in many developing countries like Egypt, the population in these places resides primarily in villages, rather than being dispersed across the countryside, and in fact the population density may be quite high in these places. In Menoufia, more than 80 per cent of the shiakha have at least 2,500 people, and nearly one-third have population densities within the built area of the village that are as high as, or higher than, those found in the suburbs of Cairo. Furthermore,

more than 90 per cent of these villages have more than 50 per cent of adult males involved in a nonagricultural economic activity.

Our analysis shows very clearly that, by every measure of urban, an urban gradient exists in the study area, going from least urban in Menoufia to most urban in the edges of central Cairo. The percentage of males not in agriculture rises slightly within the urban deciles in Menoufia, and then jumps to higher levels in the suburbs of Cairo. The percentage of females with more than a primary level of education shows a general tendency to rise slightly as the urban gradient increases in Menoufia and then it rises steeply with the increase in urbanness in Cairo. The percentage of women never married is consistently low in Menoufia and is similar to the suburbs of Cairo, but then it rises within Cairo. Conversely, the percentage of the population that is younger than age 15 is consistently high in Menoufia and similar to the levels in the lower urban deciles of Cairo, and then it drops as the urban deciles increase within Cairo.

This chapter has thus demonstrated the way in which the extraction of data from remotely-sensed images can increase our quantitative understanding of the nature of urban settlements. Nevertheless, there are many limitations to the analysis. The analysis is particularly limited by the modifiable areal unit problem (MAUP) defined well, for example, by Fotheringham and Wong (1991). The areas for which we have census data are those places that are defined for us by CAPMAS (Central Agency for Population Mobilisation and Statistics). The areal extent of newly defined places in the suburbs is very different from the older places in the center of the city and this complicates the analysis. On the other hand, if we are confident that the data from the remotely-sensed image can provide us with proxy data for human settlements, then we are in a position to define regular grids on the image and conduct an analysis that would dramatically reduce the impact of the MAUP because it would not be dependent on the census data and thus on the census boundaries. Our results suggest that the remotely-sensed imagery offers a very promising set of possibilities in that regard.

How to create a quantitative index of the urban gradient that best combines the variables is also open for discussion. We have employed an essentially reductionist approach in this analysis by using principal components analysis, but there are numerous other ways that indices could be constructed. The task ahead will be to see if several different methods yield similar results, increasing our confidence in the robustness of the use of remotely-sensed images. Although we cannot yet claim that the same classification scheme will lead to the same interpretation of urban areas in every area of the world, a fuzzy-set approach may allow us to make similar kinds of distinctions about urbanness in geographically very different places. Thus, we were able to show that Menoufia is predictably less urban than Cairo, but that the more urban places in Menoufia are similar to the less urban places in Cairo.

Data from the remotely-sensed images can be used in the analysis of urban processes such as urban sprawl (including exurbanization and an assessment of periurban areas), counterurbanization, and multinucleation. We require data from two or more dates in order to conduct such analyses, because it is change in places over time that we must measure. These analyses essentially measure the impact of human settlement by quantifying the change in the environment occasioned by human activity. This serves as a remotely-derived proxy for human behavior taking place on the ground that we might not otherwise be in a position to measure. Thus, the analysis of remotely-sensed images, and their inclusion in a geographic information system, offers us an additional set of data and insights by which to understand the nature and dynamic processes of human settlements and may offer ways of detecting change in the urban environment that is not measurable by other means.