MEASURING TEMPORAL COMPOSITIONS OF URBAN MORPHOLOGY THROUGH SPECTRAL MIXTURE ANALYSIS: TOWARD A SOFT APPROACH TO CHANGE ANALYSIS IN CROWDED CITIES

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1. ABSTRACT

This paper reports on preliminary results from a study applying the technique of spectral mixture analysis (SMA) to the measurement of temporal changes in the composition of urban morphology in the metropolitan area of Greater Cairo, Egypt, between 1987 and 1998. Although several remote sensing techniques have been successfully used for urban change analysis, most of these focus on change 'between' classes measured in a discrete, crisp way through which each pixel is assigned a label indicating either a change or no change in the class to which the pixel originally belonged. In many major cities such as Cairo, change also occurs within classes (e.g. vertical growth of buildings, increase in housing density, decrease in open spaces) and is reflected by an aggregation of land cover and urban materials. None of them may seem important in isolation. Rather, the significance of these components arises from the way they interweave with each other to structure the morphology of the urban place. In this paper, we present a 'soft' approach to detect and measure the composition of changing morphology from multi-temporal, multi-spectral satellite images. We show how SMA is capable of deriving spatially continuous variables quantified at the sub-pixel level. These variables represent measures that can be compared across urban places and at different time periods. They can be readily integrated into a wide range of applications and models concerned with physical, economic, and/or socio-demographic phenomena in the city.

2. INTRODUCTION

It has been widely recognized that satellite imagery represents an important source of information for urban analysis (Jensen *et al.* 1983, Liverman 1998, Jensen and Cowen 1999, Donnay *et al.* 2001). The timely and spatially explicit characteristics of RS data not only provide a means of exploring and testing hypotheses and models about urban areas, but also for constructing new theories that can help in the formation of policy in anticipation of the problems that accompany urbanization processes. In the case of the changing urban morphology, a considerable number of recent studies have been carried out to utilize satellite RS data in the analysis of urban change (e.g. Kwarteng and Chavez 1998, Costa and Cintra 1999, Chen *et al.* 2000, Ward *et al.* 2000, Batty and Howes 2001, Madhavan *et al.* 2001, Yang and Lo 2002). A review of such studies indicates an overwhelming focus on the temporal dynamics of urban growth such as the phenomenon of urban sprawl and the loss of agricultural land. This trend is fuelled by growing global concerns about such issues as sustainable development, environmental degradation, and global climatic change (Roberts *et al.* 1998a, Weng 2002), and motivated by the relative simplicity of replicating approaches originally designed for the analysis of change in the natural environment (Yuan *et al.* 1998). Further, the drastic spectral differences between urban elements and features from the natural environment diminish our ability to derive a straightforward interpretation of the change resulting from urban growth in terms of land cover conversions.

Patterns of change resulting from the internal modification of urban morphology, however, have received little attention within the remote sensing arena. Urban morphology can change over time as new urban fabric is added and as the existing fabric is internally modified (e.g., new buildings replace old ones, plots are amalgamated or subdivided, street layout is modified) (Knox 1995, Cadwallader 1996). These internal modifications are of a major concern because they represent the outward physical manifestation of a range of social, economic, cultural, and political dimensions associated with urban dynamics. Urban morphological changes may be detected using remote sensing when land use/land cover transitions from one type to another, or when the intensity of a given land use or material composition changes within a particular class. Many of the currently available urban change-detection methods (e.g. Jensen and Toll 1982, Ridd and Liu 1998, Bahr 2001, Madhavan *et al.* 2001) tend to overlook within-class changes and allow only a crisp or a hard assessment of change (i.e., change/no-change) (Foody 1999). Accordingly, an important aspect of contemporary urbanization dynamics related to the physical nature of internal change in urban morphology is poorly understood due to the limitations of crisp assessments in this regard.

In this paper, we address these limitations imposed by the crisp assessments of urban change by proposing a 'soft' approach to the analysis of temporal compositions of urban morphology using multitemporal, multispectral images with medium spatial resolution. Through this approach, the physically varying character of urban morphology is first quantified through single-date spectral mixture analysis (SMA). Changes in urban morphological patterns are then identified as changes in the resultant multitemporal SMA spectral fractions that represent urban land cover. For each type of land cover, change is presented as a continuum that ranges from no alteration, through modifications of variable intensity, to a full transformation of one land cover category into a different category. Once the changes are calculated, the relative contribution of each type of land cover to the overall change in morphology is identified with a given degree of certainty through a fuzzy possibilistic approach. Through the fuzzy approach, the amount of change in a land cover is expressed in terms of its degree of membership in a specific class of magnitude (e.g. high increase, lower decrease, no change, etc).

3. STUDY AREA AND DATA

The urban area of Greater Cairo represents the governorate of Cairo on the east side of the Nile River as it travels through the metropolitan region, the portion of the governorate of Giza that is along the west bank of the Nile River within the metropolitan region, and the southern tip of the governorate of Qalyubia—which currently represents the northernmost reach of Greater Cairo. The location of the study area is shown in Figure 1. The area covers 22.9 km *x*22.2 km) and includes a variety of land uses associated with a complex mix of land cover. The Mukatim desert occupies the southern part of the scene whereas the northern part includes a green belt comprising agricultural fields that are continuously being intruded by urbanization. The urbanized areas are located at the center of the scene. In these areas, residential use is often mixed with commercial, public, and sometimes "light" industrial uses within the same block. However, variations can easily be observed between: (a) affluent residential areas (sites 1 to 4 in Figure 1) with 'relatively' lower density of population (6,300 people/km^2); (b) less affluent residential areas in the old part of the city (sites 7 to 11) with higher density (44,800 people/km^2); (c) the central business district (CBD) of the capital (site 5); and (d) newly developed lands and informal settlements on the urban/rural fringe (site 6).

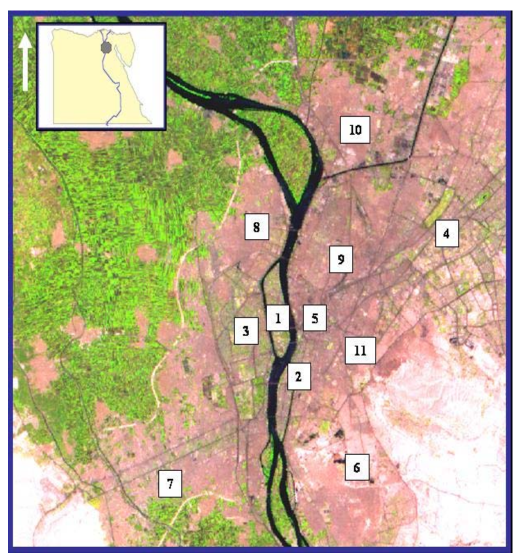


Figure 1: Study area in Cairo

Two multispectral images have been utilized in this study. The first is a Landsat Thematic Mapper (TM) image acquired in 1987, June, and the second is an Indian Remote Sensing Satellite (IRS) 1C image acquired in 1996, August. The latter covers three bands in visible (520-590) and 620-690, near infrared 770-860 nm - 23.6 m spatial resolution) and one band in short-wave infrared (1550-1700 nm - 70.8 m spatial resolution). The acquisition dates correspond as closely as possible to the 1986 and 1996 Egyptian censuses.

4. METHODS

4.1. Approach

As shown in Figure 2, the proposed soft approach to urban change analysis is a multistage process that starts with the selection of single-date image endmembers from the individual multispectral images, followed by the application of single-date SMA models in order to estimate endmember fractions that represent a direct measure of the physical abundance of different types of urban land cover at a single point of time. A good SMA model is one that produces physically realistic fractions (i.e. between 0% and 100%) and measures of error less than a certain threshold (e.g. RMS < 5 DN) (Roberts *et al.* 1998a). Next, a direct measure of change in urban morphology is calculated in terms of changes in the resultant fractions. Finally, pre-defined fuzzy membership functions representing various magnitudes of change are applied to the measures of change in endmember fractions. These functions characterize the magnitude of change in each type of urban land cover according to a threshold that indicates a specific degree of certainty.

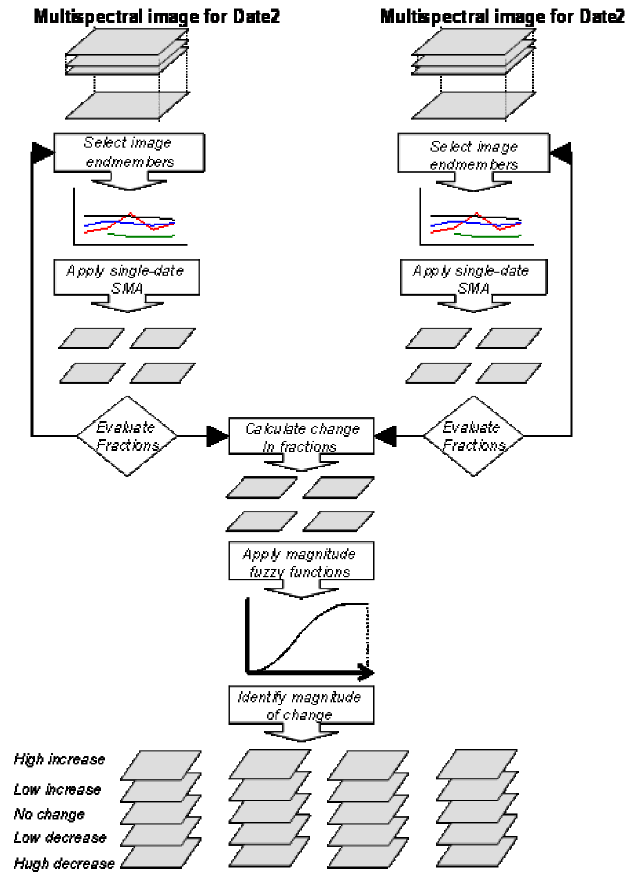


Figure 2: Flow chart for the proposed approach

4.2. Spectral Mixture Analysis

The first stage of our soft approach to the analysis of change in urban morphology was to conduct a single-date SMA on each image. The majority of SMA applications have been directed toward the natural environment (e.g. Adams *et al.* 1993, Tompkins *et al.* 1997, Roberts *et al.* 1998b, Rogan *et al.* 2002), but some recent studies have indicated the feasibility of this technique in the urban environment (e.g. Ward *et al.* 2000, Madhavan *et al.* 2001, Rashed *et al.* 2001). Mixing models are based on the assumption that the landscape is formed from continuously varying proportions of idealized types of land cover with pure spectra, called *endmembers*. Endmembers are features recognizable in the scene as being abstractions of land cover materials with uniform properties. Through SMA, the areal fractions of the endmembers are quantified at the sub-pixel level, allowing inference of the morphological characteristics of an urban landscape in terms of endmember composition. Linear SMA is the process of solving for endmember fractions, assuming that the spectrum measured for each pixel 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). Successful SMA application to change analysis relies on the accuracy of endmember selection. The selection of Endmembers can be selected in two ways (Adams *et al.* 1993): (1) by deriving them directly from the image (*image endmembers*), or (2) from field or laboratory spectra of known materials (*reference endmembers*). In the present study, we have relied exclusively upon image endmembers extracted independently from the images because of the varying spectral and spatial resolutions between the two multispectral images which impose a great difficulty on the standardization of the images. The details of the SMA procedure are discussed elsewhere (Rashed *et al.* 2001). But it is worthwhile to highlight here some important aspects to demonstrate how it was possible to derive comparable SMA measures from two multispectral images processed independently.

The conceptual model used to identify this set is the VIS model of Ridd (1995). 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*, *Impervious surfaces*, and *bare Soil*. The VIS model represents the composition of an urban environment as a linear combination of these three types of land cover thus offering an intuitively appealing link to the spectral mixing problem. Hence, the spectral contribution of its three main components can be resolved at the sub-pixel 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), Thailand (Madhavan *et al.* 2001), and Egypt (Rashed *et al.* 2001). The results show that the model is robust in a variety of urban environments, although the model may require an additional component (e.g. water/shade) to achieve an accurate characterization of the morphology of non-U.S. cities. In our present research, we used the Pixel Purity Index (PPI) (Boardman *et al.* 1995) to locate image endmembers according to the modified VIS model: vegetation (V), impervious surface (I), bare soil (S) and, the modification, water or shade (used as a proximate for building heights). The PPI method allocates to each pixel in the image a score based on the number of times it is found to occupy a near-vertex position in the repeated projections of the n-dimensional data onto a randomly-oriented vector passing through the mean of a data cloud. The resulting score helps identify image endmembers because those pixels that hold relatively pure spectra will have a high score (i.e. will be found repeatedly at the extremes of the data distribution).

After identifying representative endmembers from each multispectral image, the SMA model is applied to derive endmember fractions for each date. We employed an algorithm for spectral unmixing that is based on the unconstrained Modified Gram-Schmidt least square method (Roberts *et al.* 1998a) in which fractions are constrained to sum to 1 while individual fractions are allowed to be less than 0 or greater than 1. The specific formulation can be found in Adams *et al.* (1993) and Roberts *et al*. (1998a). When the equations are applied to an image consisting of N spectral bands using a number of endmembers less than or equal to N, the output is a fraction image for each endmember and some measure of fit. Model fit is assessed in terms of two criteria: (1) whether the fractions provide realistic abundance, and (2) the magnitude of error terms. Error terms are expressed as root-mean-square errors, which provide an estimate of the average error calculated for each pixel across all bands (see Rashed *et al.* 2001). Thus, the end products from this stage are two comparable sets of multitemporal, endmember fractions derived independently from one another. Each set includes estimates of the proportion of material elements taken for a single point in time. These materials may not seem important if considered in isolation, but their significance arises from the manner in which they interweave to structure the morphology of the city.

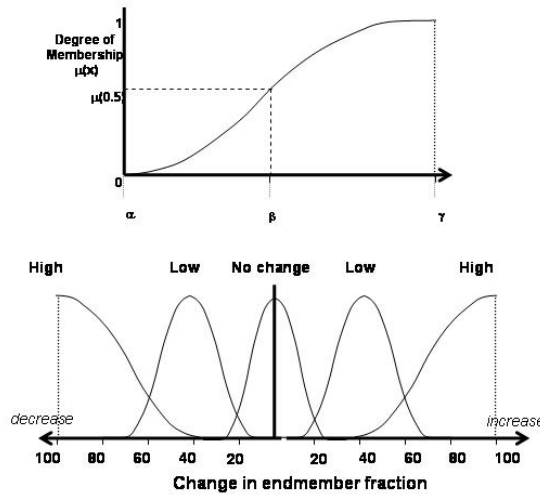
4.3. Change analysis

In this paper, we followed a pre-classification approach through which change was identified in a straightforward way by subtracting individual endmember fraction images produced from the1987 TM image, from their corresponding fractions produced from the1996 IRS image. The spatial resolution of the IRS-based bands (24m) was degraded to match the 30m resolution of the TM bands.

We recognized the uncertainties implicit in our analysis of urban change, which may result from several sources such as the use of independently selected image endmembers or from the degradation of spatial resolution of fraction bands. To address these uncertainties, we avoided estimating the magnitude of change in each land cover type through partitioning the change values in a crisp way. Rather, we adopted a fuzzy set approach to represent change in terms of various magnitudes. Fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth values between ‘certainly true’ and ‘certainly false.’ Fuzzy sets are sets without sharp boundaries in which the transition between membership and nonmembership in the set is gradual (Zadeh 1965, Zadeh 1975). This gradient, which is not a probability measure but an admitted possibility, corresponds to the degree to which an element (e.g. a pixel) is compatible with the concept represented by the fuzzy set. Fuzzy methods in remote sensing have received growing interest in recent years (Foody 1999, Mather 1999, Metternicht 1999, Zhang and Foody 1999, Foody 2001), and the fuzzy approach has been more frequently presented as an alternative to soft classification than has SMA. The two techniques have their advantages and disadvantages (see Mather 1999 for a comparison), but in the present work, we suggest that an approach in which fuzzy models operate in a subservient role to SMA models can help overcome the limitations of the two techniques.

In this research, the "fuzzification" of the bands representing the change in the multitemporal endmember fractions involved two steps. The first was to translate the concept of magnitude of change into fuzzy sets using sigmoidal (or S-curve) membership functions which are very effective in modeling continuous, nonlinear phenomena (Cox 1999). These fuzzy sets represented five linguistic concepts of different levels of change: higher increase, lower increase, no change, lower decrease, and higher decrease. An example of these sets is shown in Figure 3. Each S-curve is defined using three parameters: (1) a zero membership value (α), (2) a complete membership value (γ) and (3) an inflection point (β) which indicates at which domain value the membership degree is 0.5. The value of the curve for any domain point x is given by the following equation (Cox 1999):

$$S(x;\alpha,\beta,\gamma)=\begin{bmatrix} 0 & \rightarrow x \le \alpha \\ 2((x-\alpha)/(\gamma-\alpha)^2 & \rightarrow \alpha \le x \le \beta \\ 1-2((x-\gamma)/(\gamma-\alpha)^2 & \rightarrow \beta \le x \le \gamma \\ 1 & \rightarrow x \le \alpha \end{bmatrix}$$



Magnitude of change	Change in fraction	
Higher increase	35%	<100%
Lower increase	5%	55%
No change	-15%	-15%
Lower decrease	-55%	-5%
Higher decrease	>-100%	-35%

Figure 3. Top: An example of a fuzzy set. Middle: Five sets representing levels of change severity. Bottom: Range of fractions used in the fuzzification of different levels of severity.

The second step in the fuzzification process was to apply the fuzzy concepts of magnitude to the change bands in order to produce new bands that represent the fuzzy concepts of change severity. In order to improve interpretation of results, it was appropriate to analyze change not on a pixel-by-pixel basis, but rather at the census tract level that represents the smallest available unit accounting for the spatial variations in demographic and socioeconomic variables. This helps us establish a direct link between change in urban morphology and its underlying population forces, thus offering an effective way for the understanding of urbanization dynamics. To do so, a polygon coverage representing the census tracts was laid over the change bands produced from the subtraction of the multitemporal endmember fraction images. For each change band, the amounts of change in all pixels belonging to the same census tract were summed and the average amount of change per census tract was calculated. The fuzzy set functions indicating the different magnitudes of change were then applied to the averaged values to indicate the degree of membership of each census tract in these sets. The end product was an index of each level of change severity for each land cover assigned to each census tract. Based on these indices, we classified the census tracts according the different levels of change severity (higher increase, lower increase, no change, lower decrease, and higher decrease) based on a threshold value. This threshold indicated the degree to which we were certain about the compatibility of the final classification results with the change concepts represented by the fuzzy sets.

5. RESULTS AND DISCUSSION

5.1. SMA results

The multitemporal endmember fractions of vegetation, impervious surface, bare-soil and water/shade produced independently from the two multispectral images are shown in Figure 4. Brighter areas indicate a higher fractional abundance of the endmember while darker areas indicate lower abundance. These fractions provide a measure of the physical properties of the dominant classes in the scene at two different dates, thus helping to reveal the morphological patterns of the Cairo metropolitan area at two different snapshots in time. Some changes are readily observed in Figure 4 by the vegetation and soil fractions changing between 1987 and 1996. These changes can be attributed to the spatial expansion of the city. With the exception of these changes, the spatial patterns of the fractional abundance of all endmembers in the two dates look almost identical. For example, the active agricultural fields in the NW quadrant of the scene can be characterized in the two dates as consisting primarily of vegetation and shade with a minor amount of soil. Likewise, the central business district (CBD) of the city can be described in the two dates as having a high content of impervious surface and shade, with very low vegetation and bare-soil fractions. Further, variations between vegetation, impervious surface, and shade endmember fractions are the primary cause of physical variability among different residential districts in 1996, exactly as they are in 1987. For example, affluent residential areas can be characterized in terms of higher impervious surface, higher shade fractions, and some vegetation. This is consistent with the fabric of these areas which includes a mix of low-rise buildings, villas, high-rise structures with different building and roofing materials (e.g., steel, concrete), as well as recreational areas, sport clubs, and relatively wide boulevards. What these observations suggest is that the internal modifications that took place in the urban morphology of the city between 1987 and 1996 were partial and have not produced a major transformation in the general pattern of the city.

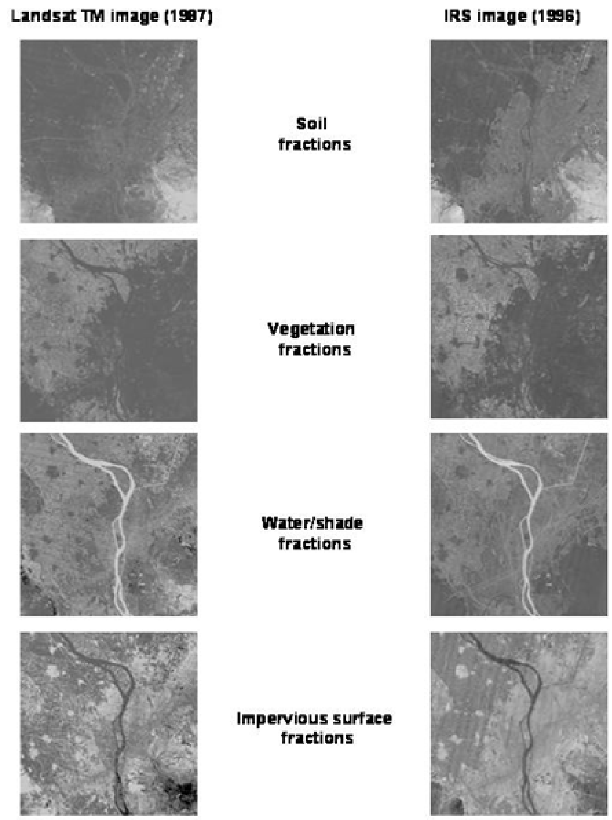


Figure 4: SMA endmember fraction images

5.2. Change analysis results

Change measures were produced by subtracting the 1987 endmember fraction images from those of 1996. Unlike other image differencing methods, the advantage of using the soft fraction images produced by SMA lies in their ability to reveal whether or not a change occurs, as well as the direction of change (increase, decrease) and the category of land cover undergoing change. The results presented in Figure 5 are based on a threshold value of 0.75. As shown in Figure 5, the severity of changes in urban land cover varies remarkably as we go from the core of the city towards the periphery. In addition, we can see that the magnitudes of change in different types of land cover are generally limited to be one of three levels: lower decrease, no-change, or lower increase. Few census tracts have higher magnitudes of decreasing or increasing land cover and they are always located on the periphery of the city. This pattern is the typical trend one can observe in large cities where rapid urban growth tends to occur first and then is followed by slower internal modification in the old fabric of the city. Of particular interest are the varying spatial patterns of change severities of land cover. In the case of vegetation, we can observe that the magnitudes of change are in general low and in most cases represent a decrease or loss of vegetation that is occurring on the city edges. As one would expect, this trend is coupled with a contrasting pattern of change severity in the impervious surface, in which case lower and sometimes higher increases occur on the periphery of the city. Another interesting observation is that higher increases in impervious surface are clustered on the south-eastern corner of the scene near the Mukatim desert, while lower increases are located near the agricultural belt surrounding the northwestern part of the city. One explanation of this pattern is directly related to the limitation imposed by the spatial resolution of the multispectral images utilized in the analysis in relation to the varying character of Cairo's urban morphology. That is, change in impervious surface can easily be observed where the morphological pattern of the urban area is relatively sparse. This is the case of both the new urban development located near the Mukatim desert and the affluent district of Zamalek that is located in the heart of the city. In both cases the increase in impervious surface occurs either because a new urban fabric has formed, as in the former case, or the old fabric is modified, as in the latter case. In contrast, change in impervious surface is difficult to observe when the pattern of the urban morphology is dense. This is the case for the old city of Cairo and the popular districts of the city that are located in the northern and western sides of the scene.

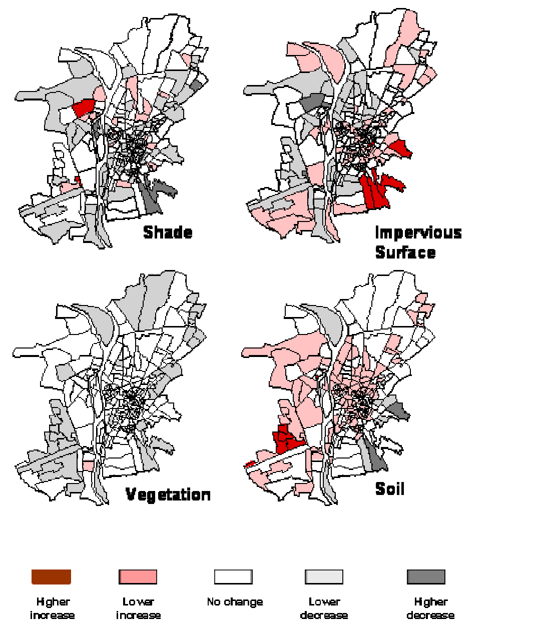


Figure 5: Study area of the Greater Cairo classified according various degrees of change severity in different type of land cover.

In terms of the change severity of both shade and soil, the contrasting patterns suggest internal modification in urban morphology resulting from modifications such as in-fill (which results in a decrease in the bare-soil) and the construction of new high-rise buildings (which results in an increase in the shade). The implication of change in these two types of land-cover, however, must be augmented by further field work and research, because both soil and shade (i.e. brightness versus darkness) are very sensitive to solar effects that were not accounted for in this study. To this end, although not done in this exploratory study, conducting sensitivity analysis by using different thresholds of 'certainty' may help identify whether the change observed represents physical change in morphology or results from limitations and errors associated with the analysis and data.

6. SUMMARY AND CONCLUSIONS

In this paper, we described a soft approach for measuring temporal changes in urban morphology through spectral mixture analysis of multitemporal, multispectral satellite images. We showed how this technique provides a direct physical measure for the basic elements that structure the morphology of the city. By decomposing the urban morphology into the same basic elements at different points of time, it becomes possible to use these standardized measures to compare the temporal patterns of morphology not only in the same city, but also between cities and even between countries. In order to illustrate an application of the approach, we used an example from the Greater Cairo region, a megacity with complex morphological patterns that are rapidly changing due to a range of complex, interrelated forces of urbanization that are poorly understood. We carried out an exercise that demonstrated how the spatially continuous character of SMA-based measures can be utilized to capture within-class changes. This type of morphological change is often neglected or assumed to be static by the crisp methods of urban change analysis. In addition to revealing the nature of internal changes in the morphology, we also identified the magnitude of these changes by a means of fuzzy set functions. We showed how the magnitudes of change can be aggregated at the census tract level to reveal a coherent story of the morphology of Cairo in which change is the rule not only on the periphery, but also in its core areas.

It has been suggested that urban morphology is 'the physical appearance of social reality' (Pesaresi and Bianchin 2001: pp 56). The potential of the soft approach to urban change analysis lies in its ability to quantify changes in the urban environment occasioned by human activity at different geographic scales. This serves as an image-derived proxy for human behavior taking place on the ground that we might not otherwise be in a position to measure. The research presented herein is a work in progress and we recognize that there are limitations in the results we presented. However, the aim of this paper is to illustrate through these preliminary results how a soft approach can offer us ways for detecting change in the urban environment that is not measurable by other means. In future research, we will explore in more detail how these remotely sensed measures can be further utilized in the study of the dynamic processes of human settlements in large cities.

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