ARTICLES

Monitoring Growth in Rapidly Urbanizing Areas Using Remotely Sensed Data

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Urbanization and the ability to manage for a sustainable future present numerous challenges for geographers and planners in metropolitan regions. Remotely sensed data are inherently suited to provide information on urban land cover characteristics, and their change over time, at various spatial and temporal scales. Data models for establishing the range of urban land cover types and their biophysical composition (vegetation, soil, and impervious surfaces) are integrated to provide a hierarchical approach to classifying land cover within urban environments. These data also provide an essential component for current simulation models of urban growth patterns, as both calibration and validation data. The first stages of the approach have been applied to examine urban growth between 1988 and 1995 for a rapidly developing area in southeast Queensland, Australia. Landsat Thematic Mapper image data provided accurate (83% adjusted overall accuracy) classification of broad land cover types and their change over time. The combination of commonly available remotely sensed data, image processing methods, and emerging urban growth models highlights an important application for current and next generation moderate spatial resolution image data in studies of urban environments. **Key Words: urban growth, remote sensing, multiscale, VIS model, cellular automata, Australia.**

Introduction

Rapidly growing regions that have major metropolitan areas in both developed and lesser developed countries face particular issues in which the spatial nature of the distribution of land cover types has environmental (e.g., transport pollution and energy use) and social (e.g., provision of services) implications. Models of landscape transformation processes that characterize the growth and internal composition of urban environments in terms of economic and biophysical information can be valuable tools to planners and managers. These types of models can be modified to utilize remotely sensed data as inputs and may provide effective ways for understanding the process of landscape transformation. A major deficiency in most of the urban planning research to date is that spatial disaggregation of projected and forecasted estimates of growth has rarely been conducted (Murray and Davis 2000). Specifically, there has not been an adequate attempt to evaluate general short- and long-term plans at reasonable scales, e.g., suburbs, with respect to future growth estimates (Fig. 1).

The need to better understand our urban environments as well as preserve natural resources has culminated in the present state of accountability, stressing that planning and management processes address issues of medium- and long-term sustainability. As an example, the southeast region of Queensland, Australia (Fig. 1) is experiencing significant population growth and questions are being raised about the social, environmental, and economic implications and sustainability of development and change in the region (Stimson et al. 1999). One of the most essential items for analyzing questions of sustainability is appropriate spatial information. Remotely sensed data are inherently suited to provide information on urban land cover characteristics related to ecological, demographic, socioeconomic, and dynamic aspects of developed regions at various spatial and temporal scales (Ridd 1995).

The development of a generally applicable

* Funding for this project was provided to Dr. Phinn and Dr. Murray through an Australian Research Council Small Research Grant. Michael Stanford provided image processing support and all image data were supplied by the Queensland Department of Natural Resources and the Australian Centre for Remote Sensing.

Professional Geographer, 52(3) 2000, pages 371 –386
Initial submission, July 1998; revised submissions, February 1999, June 1999; final acceptance, June 1999.
Published by Blackwell Publishers, 350 Main Street, Malden, MA 02148, and 108 Cowley Road, Oxford, OX4 1JF, UK.

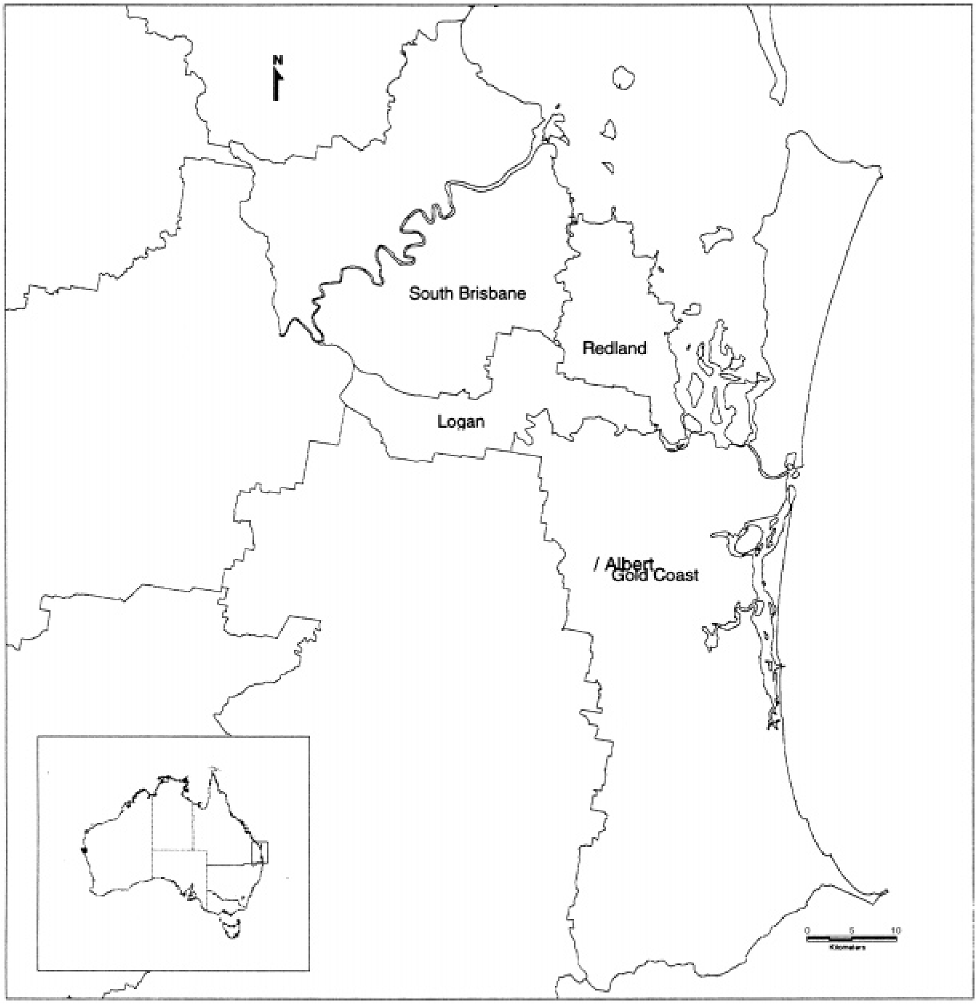

Figure 1: *Study area comprising the Local Government Areas of South Brisbane City, Redland, Logan, and Gold Coast, southeast Queensland, Australia.*

remotely sensed approach capable of both calibrating and validating models of urban growth, requires a (relatively) long-term, global collection of commonly available image data along with suitable algorithms and software. Landsat image data represent the longest archive (25 years) of moderate resolution image data with pixel sizes of 79m × 59m and 30m × 30m. Ridd (1995) developed a conceptual model for analyzing land cover types within urban areas; however, this was not presented as a generally applicable methodology for monitoring urban areas and interfacing directly with current urban growth models. Although Ridd's model intuitively links to sub-pixel scale spectral unmixing, pixel-scale image classification can also be used for monitoring and modelling urban growth at regional to suburban scales.

The work described in this paper is part of a larger project to develop approaches for utilizing remotely sensed data sources and spatial modeling techniques for regional planning. The first stage involves the development of a conceptual framework for relating urban environments to their appearance in remotely sensed images in order to calibrate and validate urban growth models. The conceptual framework for assessment of remotely sensed data has been developed for mapping the component land cover types. Further development work has focused on structuring cellular automata models of urban growth. The objective of this paper is to present a simple and robust method for delimiting the extent of urban areas and their internal composition in terms of urban (e.g., CBD, residential), rural (grassland, crops), and natural (e.g., forest) land use mixes, using remotely sensed information. For the purposes of this study, Jensen and Toll's (1982) ten stages of urban development (natural or agricultural to residential/urban) are generalized to represent most urban land cover types, with the exception of areas of completely impervious surfaces which are included as an extra class. This classification enables a definition of urban land cover type for this study as: *all impervious and landscaped surfaces associated with urban areas as well as exposed soil associated industrial sites (including quarries) and clearing for new urban subdivisions.* This approach extends the applicability of an existing model of urban land cover composition by providing a means to produce information from current and next generation satellite imaging sensors.

Background

A majority of published research focuses on the assessment of different sensor systems for classifying land cover types and their change over time, most commonly Landsat Multispectral Scanner (MSS) and Thematic Mapper (TM) (Jensen and Toll 1982; Forster 1983, 1985; Gong and Howarth 1990) and SPOT panchromatic and multispectral (Colwell and Poulton 1985; Stow et al. 1990; Wang 1990; Ridd 1995). A persistent problem in these applications is the confusion between land cover types determined from standard per pixel image classification techniques applied to multispectral, vegetation index, and texture transform images (Ridd 1995).

Although the literature on remote sensing applications in urban environments is limited in comparison to natural resource monitoring, six recurrent research themes are evident: 1) delimitation of land cover and land use types (Anderson et al. 1976); 2) assessment of the utility of texture measures and contextual classifiers to aid in separating urban land cover and land use types (Barnsley and Barr 1996; Ryherd and Woodcock 1996); 3) classifying areas of impervious and pervious surfaces for input in energy and moisture flux models (Deguci and Sugio 1994; Monday et al. 1994); 4) classifying land cover and land use change in urban areas (Jensen and Toll 1982); 5) application of empirical models to estimate biophysical, demographic, and socioeconomic variables (Weber and Hirsch 1992; Jensen et al. 1994; Mesev et al. 1995; Ridd 1995); and 6) analysis of urban heat island effects and urban morphology from thermal image data (Lo et al. 1997).

Most remote sensing applications in urban environments do not examine inter-relationships between land cover types and the natural (biophysical) and human (socioeconomic) elements of urban systems (Weber and Hirsch 1992; Ridd 1995). A number of published articles demonstrate that remote sensing techniques provide a basis for establishing fundamental land cover types of urban ecosystems. By analyzing remotely sensed data with an appropriate processing model, an objective and quantitative method may be developed for relating remotely sensed data from the urban environment to biophysical parameters relevant to thermal, hydrologic, and socioeconomic attributes (Jensen et al. 1994; Phinn 1998; Phinn et al. 1998).

The conceptual model selected to relate remotely sensed data to biophysical and socioeconomic aspects of urban or urbanizing environments represents the composition of an urban environment as a linear combination of vegetation, impervious, and soil land cover elements, i.e., the VIS model (Ridd 1995). Subdivisions of urban areas may be made based on the percentage of the spatial unit occupied by vegetation, soil, or impervious surface, as shown in Figure 2. The source of information on the distribution of these elements is remotely sensed and is subject to some form of image classification or spectral mixture analysis. Ridd (1995) established the fundamental applicability of the VIS model as a logical and quantitative means to derive biophysical information from remotely sensed data that could be analyzed to address questions on urban morphology, condition, and function. This model has not been tested outside the Salt Lake City area examined by Ridd (1995), but still exhibits poten-

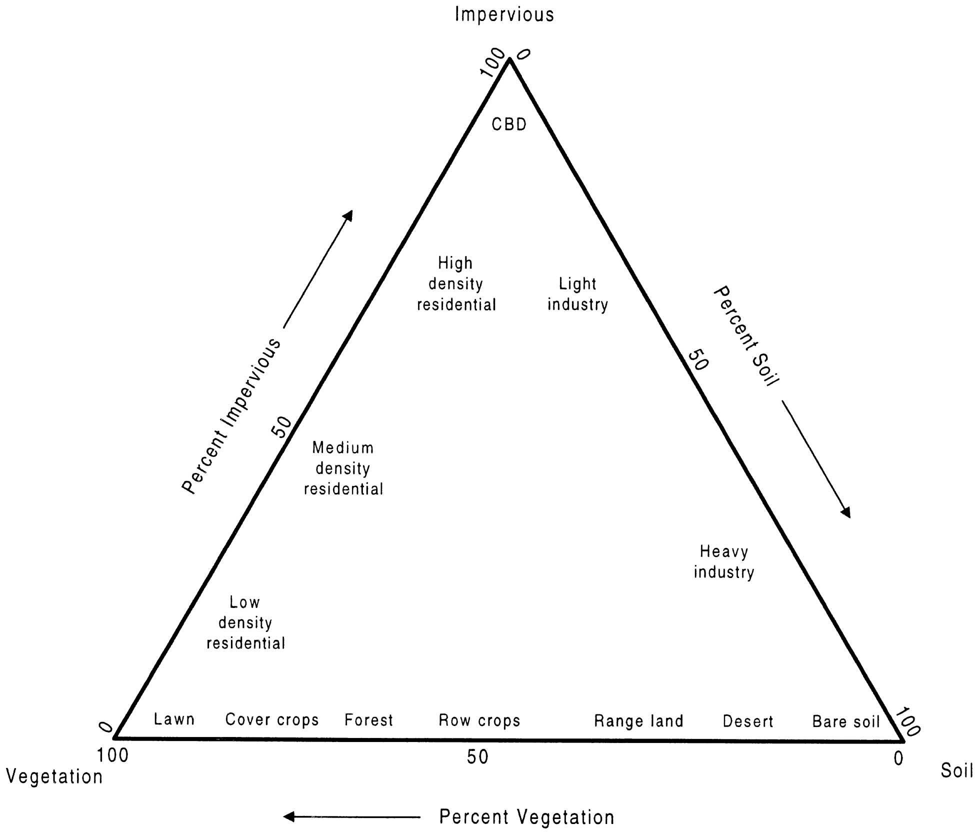

Figure 2: *Vegetation—Impervious surface—Soil model of Ridd (1995, 2173).*

tial for general application. Development of a standard approach using multispectral, moderate spatial resolution imaging systems, such as Landsat Thematic Mapper, SPOT multispectral, Indian Resource Satellite, and European Space Agency's Envisat, would provide a globally applicable scheme for mapping urban areas. These sensors will provide continuity to a long-term global database of cost-effective moderate spatial resolution images. In contrast, the next generation of high spatial resolution image data lack a long-term database and are yet to be judged in terms of cost-effectiveness for regional scale applications.

The digital photo in Figure 3 shows a portion of the study area in southeast Queensland. Each of the classes and stages of urban development shown in Figure 3 have characteristically different VIS composition. Sites 1 to 4 have high proportions of photosynthesizing green vegetation, sites 5 to 8 have varying amounts of exposed soil and impervious surfaces, and sites 9 and 10 are a mix of vegetation and impervious surface. For most remote sensing applications, each of the components of the VIS model (i.e., vegetation, soil, and impervious surface) will have significantly different spectral characteristics. Thus, by considering urban areas in the context of the VIS model, a definition of urban composition can be developed such that commonly available image processing techniques can be applied to discriminate urban land cover types.

Data and Methods

Image Data

Remotely sensed images of the study area for October 1988 and June 1995 were obtained from a fully geo-referenced Landsat 5 The-

Figure 3: *Digital orthophoto of a 3 × 3 km portion of the study area with road overlays, showing different urban land cover elements (1–10).*

matic Mapper (TM) image database, prepared by the Queensland Department of Natural Resources Statewide Land and Tree Survey (SLATS), for the state of Queensland. All images were registered to a Transverse Mercator projection, using at least 18 ground control points with a root mean square error <0.4 pixel and resampled to 25m pixel size. The images comprised TM bands 1 to 5 (blue, green, red, near infrared, middle infrared) and band 7 (middle infrared). Band 6 (thermal) was not purchased by the SLATS project, and hence was not available for the study. Band by band histogram matching was performed to minimize radiometric differences between the images. At the time of the October 1988 Landsat pass, the study area was significantly drier than in June 1995. Consequently, the 1988 image had significantly lower amounts of green photosynthesizing vegetation present.

Image Classification and Change Detection Methods

The hierarchical unsupervised image classification scheme specified in Figure 4 delineates urban land cover types. A supervised classification approach was applied initially, but failed to provide adequate separation between the target classes. The first stage of the modified unsupervised classification process involved segmenting the image into vegetation, water, and soil-impervious surface classes. For Landsat TM imagery normalized difference vegetation index (NDVI), band 5, and band 3 are commonly used for vegetation classification. Unsupervised classification using the iso-cluster algorithm was applied to a composite of NDVI, band 5, and band 3 to produce 20 classes. This allows separation of the green photosynthesizing component of the images. A further unsupervised classification was performed on the green vegetation segment of the NDVI, band 5, and band 3 composite to allow separation of the woody and non-woody vegetation components. This was relatively easy because the woody component of the vegetation in the study area comprises primarily *sclerophyllous eucalypt* species which have distinctly different spectral characteristics from non-woody vegetation such as green crops and grassland.

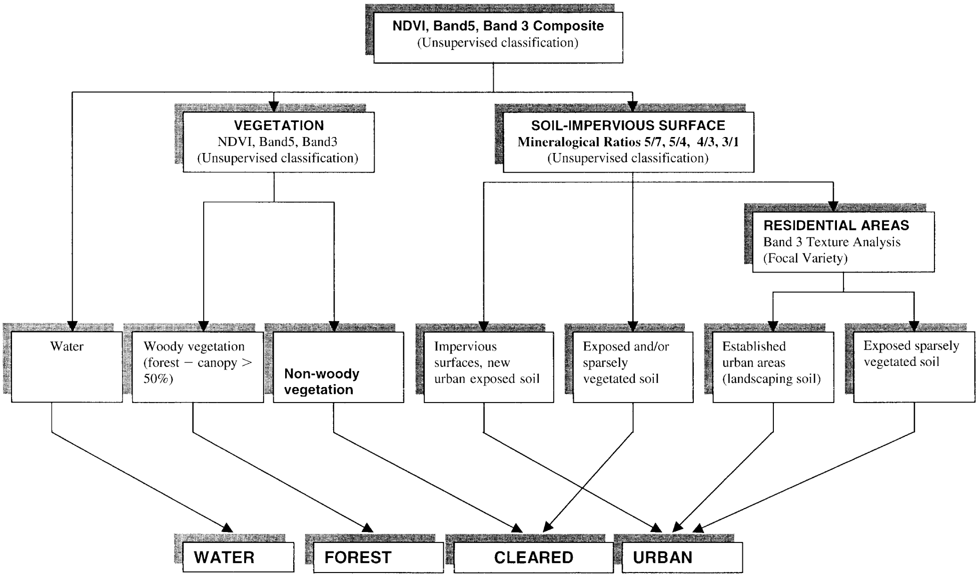

Figure 4: *Hierarchical image classification scheme applicable to Landsat Thematic Mapper image data for delimiting urban land cover types.*

Following extraction of the woody and non-woody vegetation components of the images, the remainder of the unclassified areas of the images consists of exposed soil and impervious surfaces and areas of established urban cover types comprising a spectral mix of impervious and vegetated surfaces resulting from residential landscaping. A fundamental problem faced in developing a method for classifying urban land cover is that exposed soil can belong to both the urban and the cleared classes. Important to the land cover classification method is the ability to distinguish between exposed and/or sparsely vegetated soil associated with rural or agricultural land use and exposed soil associated with urban land cover types such as industrial sites and new urban developments. Separation of these spectrally similar classes in previous applications was achieved by application of experimental contextual and fuzzy classifiers and spectral unmixing algorithms. As the focus of this project was to provide an approach that could be implemented on commonly available software for globally available image data, standard per pixel classification and spectral transformations were used.

A characteristic difference between the soils associated with urban land uses and those associated with rural and agricultural land uses is that exposed soils in the urban land use category are most often devoid of top soil and organic matter. That is, these exposed surfaces are often parent material such as clay or introduced fill used for drainage. Also, cropping in the study area tends to be limited to soils classified as rich red earth (*latosols*) which are colored by iron compounds. Mineralogical studies using remote sensing techniques have been successful at identifying a range of band ratios for Landsat TM that successfully discriminate different mineral types (e.g., ratios 5/7 for clay minerals, 3/1 for iron oxide, and 5/4 for ferrous minerals). Composite images comprising band ratios associated with mineral and hydrothermal alteration properties were developed and unsupervised classification was applied. The resulting classes allowed separation of exposed soil associated with urban land use from exposed soil associated with rural and agricultural land uses.

Having separated impervious surfaces and exposed soils associated with urban land uses, considerable confusion remained between sparsely vegetated exposed soil associated with rural land uses and established landscaped residential areas. In traversing a residential block, surface characteristics regularly change from impervious roofing and road materials to landscaped woody and non-woody vegetation within the width of one pixel (25m). Consequently, a fundamental characteristic of established residential areas with high levels of landscaping is their high frequency variability in reflectance values. This contrasts with exposed soils associated with urban land uses, which appear more spatially uniform. Using Landsat TM band 3, a measure of texture was developed that used a 150m × 150m (approximated residential block size) window to calculate focal variety (i.e., the number of different reflectance levels). The resulting texture image was classified into 20 equal interval groups and a cut-off based on visual assessment of texture was determined that separated sparsely landscaped residential from vegetated exposed soil. This allowed separation of landscaped residential areas from areas of sparsely vegetated exposed soil.

Finally, image segments were combined to produce the four primary land cover types. The forest and water classes are relatively easy to classify and drop out in the first stage of image classification. Exposed and/or sparsely vegetated soil associated with agriculture was combined with the non-woody vegetation classes (crops, grass, etc.) to produce the cleared class. Exposed soil associated with urban land uses was combined with the impervious surface and landscaped residential groups to produce the urban class. Some obvious misclassifications occurred, particularly between fallow crops and urban. Manual correction involving selection and reclassification of the incorrectly classified land cover was performed using the cluster-busting approach.

A post-classification comparison methodology was used where each pixel in the image was assigned to a new class based on its 1988 and 1995 land cover types (Dobson et al. 1995). This approach was selected in preference to image differencing due to the variations in reflectance from the same land cover types between the two image dates that resulted from the 1988 image taken during a period of below average rainfall. The hierarchical classification and labelling approach allowed stringent and consistent checks to be applied on each image to verify that pixels were assigned to correct image classes.

To provide an alternative and hopefully complementary approach to evaluating the VIS composition of Brisbane's suburbs, a constrained, linear spectral unmixing algorithm was applied to the same image data set used for the classification (Adams et al. 1995). This procedure is based on the assumption that the measured reflectance value for each ground resolution element (GRE) is an area weighted sum of the reflectance from each land cover type within a GRE (i.e., vegetation, impervious surfaces, and soils). By isolating reflectance signatures for pure areas of vegetation, impervious surfaces, and soils, and constraining the sum of their areas in each GRE to one, a modified least squares approach is used to estimate the fraction or percentage of each GRE occupied by each VIS type. This algorithm was applied to the 1995 Landsat TM image used in the per pixel classification described above.

Accuracy Assessment

Error matrices for land cover classification in 1995 were produced using digital format true colour photos acquired in 1995 at a scale of 1:5,000 and referenced to the same projection and coordinate system as the TM data. Aerial photographs were not available for 1988, and hence a quantitative accuracy assessment was unable to be completed for the 1988 land cover data. Digital photos were only available for the South Brisbane City, Redland, and Logan Local Government Areas (LGA), so the Gold Coast LGA was not included in the accuracy assessment. However, given that the land cover types, image data, and classification schemes were the same for all areas, the accuracy assessment should be indicative of the whole region. A total of seven photos were sampled using a stratified random sampling approach and 387 sample points, with two photos each being in the Redland and Logan LGAs and three in the South Brisbane area.

The sampling strategy involved randomly selecting 55 sites (pixels) within areas covered by each of the photos. This produced a total of 385 sample sites. To avoid a sampling bias towards classes with the greatest area, photos were chosen such that the total area of urban, cleared and forest in the sampled areas was approximately the same. The result was that each class had greater than 100 samples (except for the water class), which fits the rule of thumb presented by Congalton (1991) that a minimum of 50 samples should be collected for each land cover class in the error matrix. Since water covers only 6% of the area and can be relatively accurately classified using Landsat TM images, it was sampled opportunistically.

Modelling Urban Growth

In the developed modeling approach, urban growth can be conceived of as a self-organizing system in which natural constraints and institutional controls associated with land use policies temper the way in which local decision-making processes produce macroscopic patterns of urban form. In our approach, a cellular automata (CA) model that simulates local decision-making processes is integrated within an optimization framework that addresses issues of sustainable urban development. In the model, CA transition rules are modified in accordance with the outcomes of the optimization of economic, social, and environmental target thresholds associated with sustainable urban development.

To simulate urban growth using CA, information on the spatial extent of the urban area at particular times is required to initialize the growth process and to check and calibrate the model (Clarke et al. 1997). Very limited information on historic urban extent exists for the study area. The remotely sensed data offers a valuable source of recent information on urban extent. For the proposed CA modeling work, the 1988 and 1995 classification maps provide base information on urban extent to initialize the growth process and change information is used to check the model output. Following model calibration and validation, simulation of different land use scenarios can be performed to reveal the implications of different land use policies. By applying the model over the period covered by image data, changes in the image data can be used to determine the accuracy of an urban growth simulation.

Results and Discussion

Figure 5 shows the results of the land cover classification of the 1995 Landsat TM image over the same area depicted in Figure 3. The urban class is split into an established residential (high levels of landscaping) class and a class that includes exposed soil and impervious surfaces such as industrial buildings. Both of these urban classes are combined into one class in the accuracy assessment, but are separated here to demonstrate the potential of this method for contributing to the classification of urban land cover types to match the VIS model and provide validation for the CA model.

The error matrix shown in Table 1 reveals an overall accuracy of 88% in image classification for the 1995 image. To obtain a measure of accuracy that includes omission (erroneously excluded elements) and commission omission (erroneously included elements) errors, the KAPPA (K) statistic was calculated:

$$K = \frac{(\text{observed accuracy} - \text{chance agreement})}{(1 - \text{chance agreement})}$$

The KAPPA statistic indicates an overall adjusted classification accuracy of 83% for the 1995 image, representing an improvement from previous classification of TM images in urbanizing areas in southeast Queensland of 69% to 75% (Phinn et al. 1998).

The difficulty in separating land cover types based on the definition of urban utilized here is reflected in the commission and omission errors shown in Table 1. The cleared class was the most poorly classified with commission and omission errors of 13% and 18% respectively. For the urban class, commission and omission errors are 9% and 10% respectively, with most of the commissions and omissions occurring with the cleared class. The majority of the confusion between urban and cleared classes occurred in distinguishing landscaped residential areas from sparsely vegetated soil. Further confusion between the cleared and urban classes occurred because of the difficulty in distinguishing exposed and/or sparsely vegetated soil. Confusion also occurred between cleared and forest classes. This resulted in commission and omission errors for the forest class of 13% and 5% respectively.

Impervious surfaces and exposed soil with little or no vegetation, such as that associated with industrial sites and new urban developments, have characteristically higher brightness values than areas containing a mix of vegetation and, with the exception of the exposed soil cover type, are relatively easy to separate. Mineralogical band ratios applied in this study proved useful in distinguishing the exposed soil component of industrial sites and new urban developments from other cleared land cover

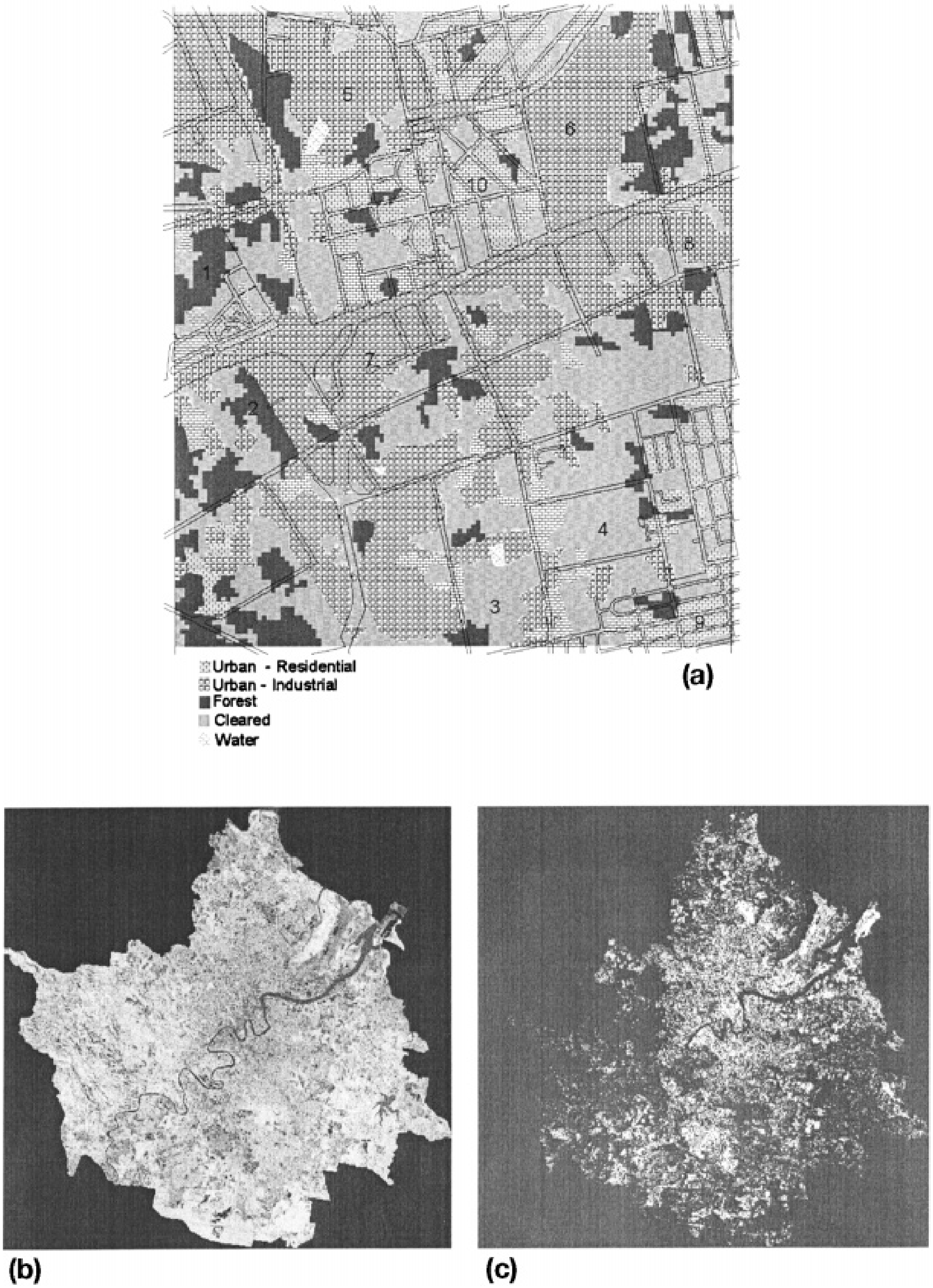

Figure 5: *(a) Land cover classification results obtained from the 1995 Landsat TM data, shown for a 3 × 3 km portion of the study area (corresponds to the area shown in Fig. 3). (b) Vegetation and (c) Soil Fraction images produced from a constrained spectral mixture analysis algorithm applied to the Brisbane 1995 Landsat TM image.*

Table 1 *Error Matrix for 1995 Land Cover Map*

	Actual						
Classified	**Urban**	**Cleared**	**Forest**	**Water**	**Accuracy**	**Omission**	**Commission**
Urban	125	11	2	—	89.9	10.1	9.4
Cleared	11	104	4	—	81.9	18.1	12.6
Forest	3	12	110	1	94.8	5.2	12.7
Water	—	—	—	3	75	25	0

types with proportions of exposed soil. For example, sites 1 and 2 shown in Figure 3 are a cement factory and brickworks respectively. Both of these sites are a mix of impervious surfaces (mainly buildings) and exposed soil with little or no vegetation or organic matter. The spectral characteristics of the soil at these sites is significantly different from site 4, which is sparsely vegetated with areas of bare crop containing amounts of organic matter. The success of mineralogical band ratios in separating the exposed soil cover type can be attributed to the significantly different spectral characteristics of soils associated with urban and rural land cover types.

In the approach we used in this study, mineralogical band ratios were classified in three band composite form, which limits the ability to discern the potential contribution of individual ratios to distinguish particular land cover types. For example, band 4/3 ratio expresses the presence of iron oxide. The characteristic red color of the latosols used primarily for cropping in the study area results because of coloring by iron compounds. Band ratios used in mineralogical studies appear potentially useful in urban classification. More information may be obtained from these ratios by using individual ratios to develop relationships for particular land cover characteristics. For example, ratio 5/7 highlights clay minerals and may be useful in distinguishing areas cleared of topsoil for new urban developments.

The confusion between the cleared class and established urban residential appears to result because pixels with a mix of impervious surface (e.g., tiled roof) and vegetation (e.g., grass), as in residential areas, have similar spectral characteristics as some areas of sparsely vegetated and/or exposed soil associated with rural land cover types. This is to be expected because only 30% to 40% of residential surface area is covered by buildings, as discussed in Jensen and Toll (1982), with the remainder of the area having similar surface characteristics to some rural land covers.

As observed in a number of other urban classification studies, texture is a useful interpretation technique for identifying urban residential land use. The simple measure of texture for determining the spectral variety in a 150m × 150m neighborhood used in this study upholds the findings of previous studies. While this measure of texture worked well in established dense residential areas, problems were encountered when housing density decreased at the urban fringe. More sophisticated measures of texture may reduce the confusion in classifying established residential areas (Ryherd and Woodcock 1996). However, this is a fundamental problem in urban classification and is intrinsically linked to the definition of urban land cover types, not land use types in urban areas. At the urban fringe the change between urban residential and rural residential is often not discrete, but rather a continuous decrease in housing density. Therefore, any measure of texture requires the development of a cut-off that delimits urban residential from rural residential and must be related to selected land cover classification. In this study 0.8 hectares was used as the minimum unit size. Thus, cleared areas (e.g., backyards) greater than 0.8 hectare that may occur between adjoining residential blocks are incorrectly classified as cleared when they are actually residential.

The relative proportions of each land cover type separated using vegetation indices, mineralogical band ratios, and texture analysis depends on the time of year the images are captured. The images used in this study were captured in June, which is a dry time of year in our study area. Consequently, the non-woody ground cover associated with cleared areas has dried off, exposing areas of soil. However, had the images been captured following the wet season, green vegetated ground cover on cleared areas would have been more complete and these areas would have been separated out using a vegetation index such as NDVI. A number of other vegetation indices (e.g., soil adjusted vegetation index) were considered for this application, but did not produce consistent results within the urban areas examined.

Post-classification change detection (Dobson et al. 1995) was applied to identify areas of urban growth from 1988 to 1995, since both images were processed using the same classification scheme. This method involves a pixel-by-pixel comparison of the 1988 and 1995 classification maps to produce a change detection matrix that represents specific "from-to" occurrences of land cover classes. Since the major focus of this work is on the land cover composition of urban areas and its change, only the results of the change in the urban class are reported here. Table 2 shows the results of the change detection for the urban class by LGA.

While being a commonly used change detection technique, post-classification change detection requires high degrees of classification accuracy and geo-referenced conformity because all errors in each classification image are present in the change detection map (Dobson et al. 1995). A particular problem faced in this classification exercise was the different levels of dryness associated with the landscape captured in each image. For the 1988 image the landscape was much drier. A consequence of this is that there is a tendency for the 1988 classification to show a greater area of urban than the same unchanged area in the 1995 classification. This is due to the fact that during drier years there is more dry vegetation and exposed soil in residential areas. This leads to differences in separating the "Established urban" and "Exposed sparsely vegetated soil" classes (see Fig. 4) for the two time periods. Both classes were still able to be grouped into an urban class, but the results highlight the need for a hierarchical approach for land cover assessment within urban areas, part of which may be addressed by spectral unmixing algorithms. A selection of the results from the spectral unmixing of the 1995 Brisbane TM image are shown in Figure 5 and depict a similar pattern to that observed in the per pixel classification, but more directly linked to the VIS model specifications. Hence, the spectral unmixing analysis could be used in combination with the per pixel classification in a post-classification refinement mode to define suburban scale cover classes and then determine their dominant composition (Fig. 5). For example, the vegetation and impervious surface fractions within areas classified as urban were used to set thresholds to identify low (vegetation > 80%), medium (80% > vegetation > 50%) and high (vegetation < 50%) density residential zones. The refined urban classification was cross-checked with aerial photographs and local knowledge and considered to be moderately accurate.

Table 2 *Area of Urban Change (>5 ha) from 1988 to 1995 by LGA*

SHIRE (LGA)	Area of Urban Change (ha) (>5 ha)	Percentage Change in Urban Area
South Brisbane City	25,289	14%
Logan	871	11%
Redland	636	12%
Albert	5344	43%

In the change detection map, differences in the classified images resulting from landscape dryness manifest as small slivers of change. To overcome this problem, the change detection image was filtered for areas of change greater than five hectares, thus eliminating the small slivers of predominantly erroneous change. A consequence of this filtering is that small areas that do show actual change, such as rural residential developments, are removed. This limitation is particularly evident in the Redland Shire which has undergone substantial rural residential development from 1988 to 1995, very little of which is evident on the filtered change detection image. In general, the area of urban change reported in Table 2 is conservative and represents change of the type shown in Figure 6, which shows the area of urban change from 1988 to 1995 as dark areas overlaid on the classification image shown in Figure 5. The urban change between sites 1 and 2 on Figure 6 resulted from the development of a major roundabout on the arterial round that passes through the image. The large area of change near site 3 is a new industrial complex. The change at site 6 probably resulted from the expansion of storage area for the brickworks. Smaller areas of change due to rural residential development or small areas of development (e.g., individual houses) on the urban fringe are not represented in the change analysis.

To demonstrate the application of classified

Figure 6: *Land cover change results obtained from the 1995 and 1988 Landsat TM data, shown for a 3 × 3 km portion of the study area (corresponds to the area shown in Fig. 3); the black areas represent pixels that changed to the "urban class."*

image data in simulating urban growth, a simple CA growth model was implemented for the Gold Coast, a rapidly growing region of the Albert Shire (Fig. 1). In the simulation procedure used here, the birth of a development unit at any time in the simulation depends on the inverse distance from an existing developed unit (Batty and Xie 1997). Constraints to growth associated with land slope, distance from the transport network, and distance from commercial centres are stochastically imposed on the simulation process when considering the birth of a development unit.

Figure 7a shows the change in urban residential extent for the Gold Coast area derived from classification of the 1988 and 1995 images. Urban residential extent is determined using zoning information for the Gold Coast local government area. If an area is zoned residential and the 1988 and 1995 classified images show the area as being urban the area is classed urban residential. Figure 7b shows the initial results of the simple CA residential growth model applied to the Gold Coast area. In the simulation, urban residential extent derived from the 1988 image classification was used to provide initial conditions for the simulation such that any mapped urban land cover type can potentially give rise to new growth (Fig. 7b). Boundary conditions that determine a stopping point for the simulation are set by the area of residential growth on the Gold Coast from 1988 to 1995. Growth is based on single cells of size 50m using resampled 1988 and 1995 classification maps. Visual calibration (e.g., Clarke et al. 1997) was used to determine the value of the parameters for each of the constraints to give the best fit to actual growth patterns.

The purpose of presenting the initial results of actual and simulated growth is to demonstrate the application of our image process-

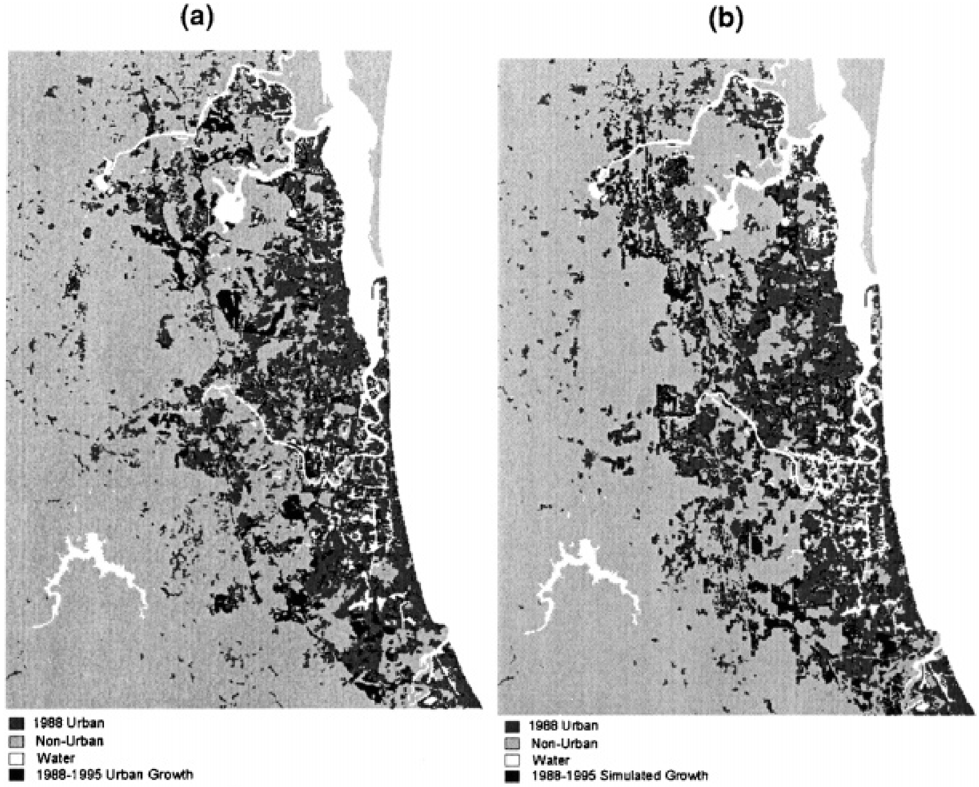

Figure 7: *(a) Change in residential urban extent for the Gold Coast area derived from 1988 and 1995 classification maps; area shown is approximately 30km × 50km. (b) Simulated change in residential urban extent for the Gold Coast area 1988 to 1995, calibrated from the 1988 image classification; area shown is approximately 30km × 50km.*

ing approach for modeling growth and to show that the simple model used here can produce realistic looking growth patterns (e.g., Fig. 7b). Omission and commission errors and agreement levels are used to assess the performance of the simulation model. The model performs reasonably well with agreement between the simulated and actual residential growth of 63 percent. A large amount of the area associated with commission errors (38%) results from overestimating the degree of "in filling" in the older established urban matrix. This is associated with the way initial conditions for the model are set using 1988 urban extent. Since the density of urban extent is greatest in the older established areas, the model tends to have rapid growth in these areas leading to an overestimation of new development in these areas. Since boundary conditions (area of growth from 1988 to 1995) define the stopping point of the simulation, omission errors (36%) will result from overestimation of the degree of "in filling."

The objective of our approach to simulating urban growth is not to predict actual growth patterns but to develop a "what if"-type planning tool such that, given population growth projections and land use constraints, possible growth scenarios can be developed and assessed. Remotely sensed data provides a realistic calibration source for the model (distribution of urban and non-urban land cover types) and a validation source for model output over a set period. In developing this application the processed remotely sensed data are explicitly matched to the input requirements of the CA model in terms of defining the spatial distribution of urban and non-urban land cover types. In further development of the CA growth model, the size of the neighbourhood in which a birth can occur will be varied to give different densities of development units. The current constraint that a birth of a new development unit requires the existence of a developed unit will be relaxed such that new development can occur independently of existing developed units. The growth model will be linked to a model of population projections to allow the exploration of possible growth scenarios that take into account local government strategic plans.

Conclusions and Future Research

The results obtained from this application of Landsat Thematic Mapper (TM) image data indicate that the land cover type composition of an urban area and urbanizing areas can be successfully classified using a carefully designed image processing methodology. This methodology should be globally applicable given its reliance on moderate spatial resolution image data and a combination of standard image processing operations. Changes in the composition may also be classified over time to provide a basis for examining the dynamics of urban growth, but the accuracy of these analyses is highly dependent on the accuracy of the original images of land cover types. As a consequence of the heterogeneous nature of land cover types in urban areas, sub-pixel scale effects tend to be averaged out in per-pixel classification algorithms and very broad land cover classes are the only accurate cover types capable of being produced. Each of these broad land cover types can be considered in terms of their component vegetation, soil, and impervious surface characteristics as quantified by the spectral unmixing algorithm. Classifying the VIS composition of urban and urbanizing areas should provide a more meaningful approach to assessing internal variation within urban areas from traditional regional scale imaging sensors, such as Landsat TM and SPOT, and the next generation of high spatial resolution imaging sensors (Jensen and Toll 1982; Ridd 1995). In particular, the VIS approach and the classification scheme developed in this paper build upon a definition of urban areas relevant to spatial and spectral characteristics of remotely sensed imagery, and are inherently suited for incorporation into models of urban growth.

In relation to urban remote sensing applications, the findings presented here are a preliminary step in the process towards a comprehensive multiscale approach to classifying land cover types in urban areas and their change over time. Results from the classification process were explicitly matched to the calibration and validation requirements of a cellular automata (CA) model of urban growth. Hence, significant operational extensions were provided for the VIS model of Ridd (1995) and the popular CA approach to urban growth modelling. The hierarchical classification approach identifies urban areas and their internal land cover composition, building upon earlier works of Jensen and Toll (1982) and Ridd (1995). Successful results were obtained using the output from the image classification and change detection to calibrate and validate a cellular automata model of urban growth. Work is continuing on the development of the methods for assessing urban composition, combining Landsat TM and higher resolution data, calibration of a cellular automata model of urban growth using image data, and comparative assessment of VIS analysis results between southeast Queensland and North American cities. ■

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