Spatial Composition of Spectral Classes: A Structural Approach for Image Analysis of Heterogeneous Land-Use and Land-Cover Types

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Abstract

Spectral classes generated from image classification are conventional output in land-use and land-cover (LU/LC) mapping with digital remotely sensed data. The spatial composition of these spectral classes within a certain spatial range, or window, can be useful information for image analysis. In this study, the concept of spatial composition of spectral classes (SCSC) was developed and examined. It was found that LU/LC types did exhibit different characteristics of SCSC. Ranges of SCSC were used for post-classification labeling to identify different LU/LC types. Results showed that a 7 by 7 window size was suitable for Hong Kong at Level-II classification.

Introduction

Remotely sensed data have been widely used to generate land-use and land-cover (LU/LC) maps. High spatial resolution satellite imagery acquired by Landsat Thematic Mapper and SPOT HRV have provided spatial details for image analysis so that high frequency features can be identified. However, for many ground scenes, conventional per-pixel digital image classification techniques may not be appropriate because of spectral heterogeneity of features on the ground (Woodcock and Strahler, 1987). Spectral heterogeneity is related to high frequency features which are the joint effect of improved sensor resolution and complexity of ground features. High frequency features are especially pronounced in high density urban areas where various land-cover types tend to be intermingled with or occur adjacent to each other, and appear as a composite. To enhance our understanding of the structure of these features in images and to improve classification results, various attempts have been devised.

Texture has been widely used to characterize the spatial variation of radiance values in a neighborhood of pixels. Haralick (1979) reviewed commonly used textural measures, including those derived from spatial statistics, grey-level co-occurrence probabilities, and power spectrum. Conners and Harlow (1980) examined and compared different textural algorithms based on the amount of texture-context information obtained. Woodcock and Strahler (1987) used local variance to measure the spatial structure of images as a function of spatial resolution. Textural measures have also been incorporated into multispectral data for classification (Franklin and Peddle, 1989; Gong and Howarth, 1990) and change detection (Fung and LeDrew, 1987).

There have been studies in the use of semivariograms to analyze the spatial information inherent in digital images (Curran, 1988; Woodcock *et al.*, 1988a; 1988b). Semivariograms have been applied to image resampling problems (Ramstein and Raffy, 1989), to develop procedures for sampling of remote sensing data (Atkinson *et al.*, 1990), and to study forest canopy structure (Cohen *et al.*, 1990).

More recently, the application of fuzzy set theory has been found to have potential in enhancing classification results. Fisher and Pathirana (1990) found the fuzzy classifier helped extract information of both individual pixels as well as subpixels. Wang (1990) also found that the fuzzy membership of pixels offered information about the component cover classes of mixed pixels.

These studies reveal two basic issues associated with high frequency features. First, mixed pixels appear as each pixel records the radiant energy reflected by a composite of ground features. The resultant pixel does not record the spectral reflectance of one particular feature but is a weighted sum of reflectances of various features.

Second, given an area or polygon of a particular LU/LC, e.g., residential land, a high variation of spectral reflectance is found as each pixel may record reflectances of different ground features. For instance, residential land is composed of buildings, shadows of the buildings, trees, roads, etc. Spectral reflectances of these features differ, giving rise to a situation where two adjacent pixels may record reflectances from two different features (e.g., buildings and grass lawns). The result is a great spatial variation of spectral reflectances within the area of residential land. Applying a per-pixel classification will most likely generate several spectral classes for this LU/LC. This effect is critical if the high resolution data (e.g., SPOT HRV) is used to map general LU/LC types (Level-I classification) such as urban land. The same effect perpetuates in more detailed LU/LC types (Level-II classification) such as low density residential land, high density residential land, or industrial land.

In this paper, we attempt to investigate this second issue

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Photogrammetric Engineering & Remote Sensing,
Vol. 60, No. 2, February 1994, pp. 173–180.

0099-1112/94/6002–173$03.00/0

of spatial variation of spectral information. Most remote sensing studies apply radiance values recorded by sensors for analyses. To investigate spatial variation of spectral data, textural analysis is commonly used. We adopt a different and simplified approach. Instead of studying the raw radiance values, spectral classes yielded from unsupervised classification are examined in terms of their composition in a spatial context. The objectives are to investigate (1) whether the spatial composition of spectral classes (SCSC) can be useful information for characterizing LU/LC types, particularly those heterogeneous ones; and (2) whether this information can be used for post-classification labeling, or as a means for map generalization, particularly for the general LU/LC types at Level-II classification in Hong Kong.

Spatial Composition of Spectral Classes

Any per-pixel image classification yields a number of classes. These classes are called spectral classes because they are derived directly from partitioning data in the spectral domain according to certain decision rules (Richards, 1986). These spectral classes are meaningful when they can be directly associated with a particular type of LU/LC.

A high frequency feature or a feature of high spectral heterogeneity exhibits a high local variance (Woodcock and Strahler, 1987). Suppose a per-pixel image classification is performed on this feature; it will most likely be represented by several spectral classes. This means that heterogeneity is indeed reflected by a composite of spectral classes. For instance, spectral classes within a high density residential land may represent narrow roads, buildings, shadows of these buildings together with a distribution of vegetation planted along roads or in parks. Some of the spectral classes derived may not be meaningful. For instance, building shadow is not a real land-cover type but an artifact of tall buildings and the image acquisition process. The per-pixel based classification may not easily provide information about this LU/LC of interest. However, the spectral classes generated may shed new light on characterizing this type of heterogeneous LU/LC.

In other words, in addition to radiance values, we can investigate the SCSC of LU/LC types. We can define any LU/LC type according to the following:

$$LU_i = f\{SC_1, SC_2, ..., SC_n\} \quad (1)$$

where LU_i is the LU/LC type i and SC_1, SC_2, ..., SC_n are spectral classes derived from a per-pixel classification.

A spectrally heterogeneous LU/LC is, therefore, a composite of several spectral classes. It does not necessarily include every spectral class produced from the original image classification. But there exist several (or one) predominate spectral classes which characterize it. A homogeneous LU/LC type is, therefore,

$$LU_o = f\{SC_K\} \quad (2)$$

where the homogeneity of this type is reflected by the representation of one and only one spectral class, K.

A similar study using cover-frequency with a minimum-city-block classifier was carried out by Gong and Howarth (1992) which result indicated a significant improvement over supervised maximum-likelihood classification. Janssen *et al.* (1990) used a different approach in which the composition of spectral classes was derived based on object boundaries of GIS data. The label of each object was determined based on the largest frequency within the object boundary. They found that the resultant overall accuracy increased over 10 percent as compared with that of per-pixel classification.

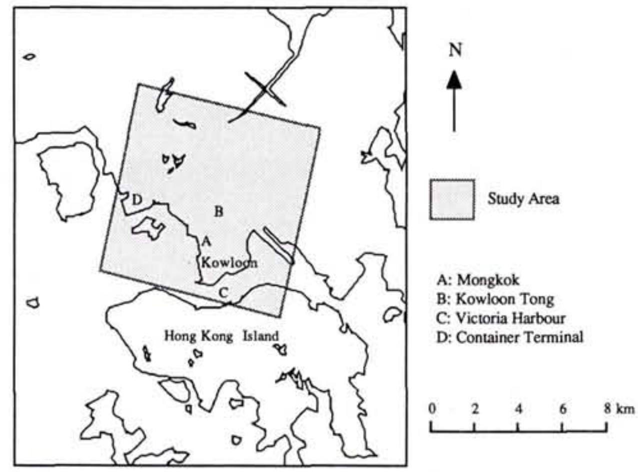

Figure 1. Area covered by 512 by 512 pixels of SPOT image used in the Study.

Methodology

Data Description

A SPOT HRV multispectral (XS) image of Hong Kong acquired on 14 January 1987 was used for this study. A study site of 512 by 512 pixels centered at 22°20'N, 114°10'E covering the Kowloon Peninsula and northern part of the metropolitan area of Hong Kong Island (Figure 1) was extracted for image processing.

With reference to the 20-m spatial resolution of SPOT HRV data, LU/LC types at Levels-I (e.g., urban land) and II (e.g., high density residential land, low density residential land, and industrial land) in this area exhibit a wide range of spectral heterogeneity. A relatively homogeneous class is water. As an important port in East Asia, water constitutes a large proportion of the area in Hong Kong. In Victoria Harbour, however, homogeneity does decrease with the presence of vessels and ferries. As a contrast, many other LU/LC types are characterized with a high degree of spectral heterogeneity. In the highly dense mixed residential and commercial district of Mongkok, multi-story buildings of various heights ranging from 10 m to 70 m, together with their shadows, give rise to great ranges of grey tone in all three multispectral bands. In another low density high class residential district of Kowloon Tong, buildings of 2 to 4 stories are intermingled with road networks and a luxurious growth of vegetation in lawns and gardens. The great variation in spectral heterogeneity makes this site a suitable area for examining the SCSC of various LU/LC types in Hong Kong.

Generation of Spectral Classes

The first step towards an analysis of spectral composition is the derivation of spectral classes. An unsupervised classification based on a K-means clustering with a maximum-likelihood classification routine was performed. A total of 40 spectral classes was derived. A bi-spectral plot of mean vectors (Figure 2) of these spectral classes was plotted for a cross examination together with the classified image (Figure

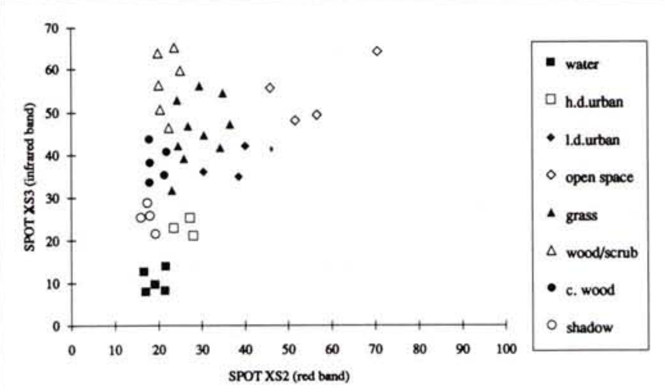

Figure 2. Bi-spectral plot of spectral classes derived from unsupervised classification.

3). They were then categorized and labeled into eight spectral classes. They are

- water
- high density urban land
- low density urban land
- open space/bare soil
- grass
- woodland and scrub
- coniferous woodland
- woodland on shadowed slope

The classified image was subjected to accuracy assessment. Reference information includes color aerial photographs taken in 1986 and 1988, 1:5,000- and 1:20,000-scale topographic maps, land-use maps, and field surveys. Owing to the extensive coverage of water in the study area, sampling was taken based on test sites. According to the nature of spectral classes, two to three test sites were selected for each class. Random samples were taken within each site, resulting in a total of 2327 sample pixels for the eight classes. These pixels were checked against the reference information to generate a reference image for accuracy assessment of the classified image. An error matrix together with the overall accuracy and Kappa coefficient of agreement were computed (Congalton, 1991).

SCSC in Test Sites

To investigate the SCSC of various LU/LC types, 20 test sites were identified based on a cross examination of the reference information. These sites represented various LU/LC types of the study area and were independently selected from those chosen for accuracy assessment. They were delineated as polygons on the image with their sizes ranging from 24 to 147 hectares (Table 1). Each site was studied in terms of

- its overall composition of spectral classes and
- the variation of SCSC along selected transects.

Frequencies of the spectral classes were computed for each test site from which proportions of them within the sites were generated. Figure 4 illustrates the SCSC of the 20 test sites. Table 1 shows the description of these sites.*

It should be noted that SCSC extracted from the test sites is a generalized statistic. Great local variations exist within some of the sites. To study their internal variation, transects were selected from the image for each site. These transects were selected manually such that they were the longest possible transects within the corresponding test sites. Each tran-

*For clarity, spectral classes in the paper are printed in lowercase (e.g., water) whereas LU/LC types are printed in UPPERCASE (e.g., WATER).

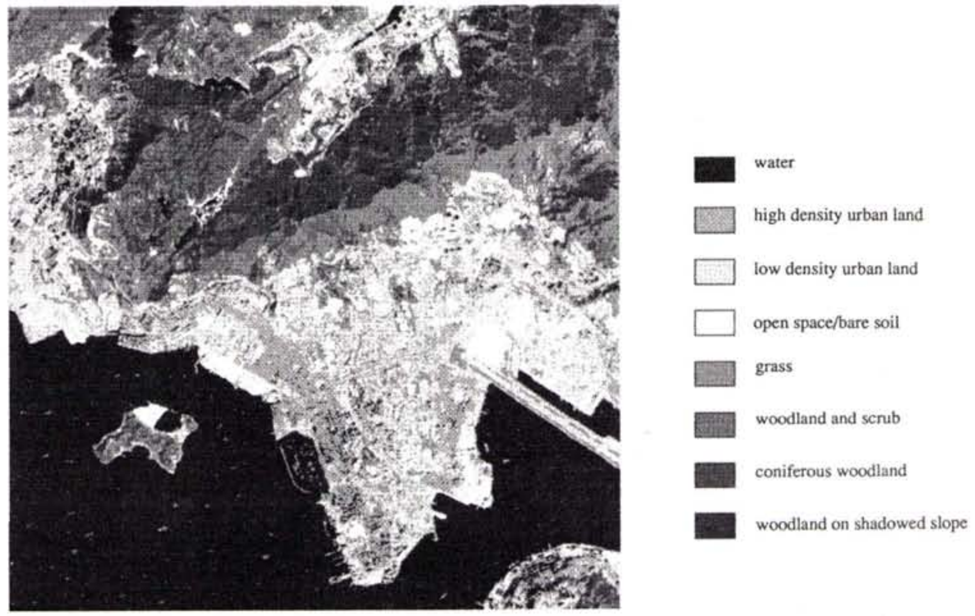

Figure 3. Classified image from per-pixel unsupervised classification.

TABLE 1. DESCRIPTION OF THE 20 TEST SITES

Site No.	Description	Area (in hectares)
1	turbid water	54.1
2	clear water	147.4
3	water/boat shelter	37.2
4	reservoir	30.7
5	low density high class residential land	45.9
6	public housing estates	36.9
7	high density mixed residential and commercial land	68.2
8	high density mixed residential and commercial land	33.0
9	commercial land	26.5
10	squatters	24.0
11	public housing estates	37.0
12	industrial estates	81.8
13	industrial area/container terminals	61.3
14	reclamation area	24.8
15	airport	27.7
16	airport/runway	73.0
17	woodland/scrub	30.6
18	woodland/scrub	30.6
19	coniferous woodland	56.5
20	grass	60.8

sect stretched from one boundary, passing through the center and reached another boundary of the test site. Thus, variation of SCSC can be examined from the boundary to the center of transects.

Along each transect, moving windows were used to extract the SCSC information for each pixel. Window sizes of 3 by 3, 5 by 5, 7 by 7, 9 by 9, and 11 by 11 were used. Using different window sizes helps to explore at which size the window will be most suitable to characterize the LU/LC types based on the SCSC information. For illustration, Figures 5a and 5b show the variation of SCSC along transects for the test sites of (a) LOW DENSITY HIGH CLASS RESIDENTIAL LAND (Site No. 5) and (b) HIGH DENSITY MIXED RESIDENTIAL AND COMMERCIAL LAND (Site No. 7) with window sizes from 3 by 3 to 9 by 9. From these transects, it is possible to extract the ranges of SCSC of the LU/LC types. These ranges of SCSC can also be compared with the exact proportion obtained from the entire test sites (Figure 4).

Application in Post-Classification Labeling

From the analysis of spectral composition of different LU/LC types, it is possible to derive simple rules for post-classification labeling. For a given window size w by w, we can identify a pixel x_j as belonging to LU/LC i if the composition of various spectral classes falls within certain ranges: i.e.,

$$x_j \in i \qquad \text{if} \left\{ \begin{array}{l} r_w(\mathrm{SC}_{nl}) < p_w(\mathrm{SC}_n[x_j]) < r_w(\mathrm{SC}_{nh}) \\ r_w(\mathrm{SC}_{2l}) < p_w(\mathrm{SC}_2[x_j]) < r_w(\mathrm{SC}_{2h}) \\ \cdots \quad \cdots \quad \cdots \quad \cdots \\ r_w(\mathrm{SC}_{1l}) < p_w(\mathrm{SC}_1[x_j]) < r_w(\mathrm{SC}_{1h}) \end{array} \right\} \tag{3}$$

where $p_w(\mathrm{SC}_n[x_j])$ is the proportional composition of spectral class n for pixel x_j within a window size of w by w, and $r_w(\mathrm{SC}_{nl})$ and $r_w(\mathrm{SC}_{nh})$ denote the lower and upper limits of the range of composition for spectral class n derived from data analysis of the test sites. This process resembles the use of a simple parallelepiped classifier.

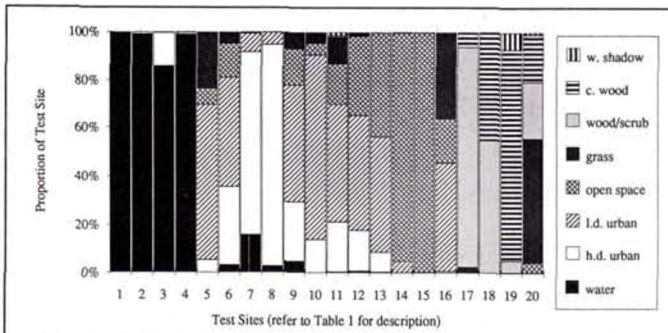

Figure 4. Spatial composition of spectral classes of the 20 test sites.

Because most LU/LC types need not be characterized by all the spectral classes, decision rules can be designed using the most predominate spectral class(es) only. In reverse, we can identify a pixel x_j as belonging to LU/LC i if its SCSC does not include spectral class c: i.e.,

$$x_j \in i \qquad \text{if } \{p_w(\mathrm{SC}_c[x_j]) = 0.0\} \tag{4}$$

Decision rules may also be structured based on a ratio of different spectral classes. For instance,

$$x_j \in i \qquad \text{if} \left\{ \frac{a_2 p_w(\mathrm{SC}_2[x_j])}{a_1 p_w(\mathrm{SC}_1[x_j])} > k \right\} \tag{5}$$

where a_1, a_2, and k are constants.

To implement the rules, they were designed in a hierarchical structure which helped simplify the classification process. In the initial stage, vegetation related spectral classes were used as criteria to differentiate vegetative features from those not covered by vegetation. More detailed decision rules were then set to classify specific LU/LC types. The rules derived for post-classification labeling with a window size of 7 by 7 were listed in Figure 6.

Ten Level-II LU/LC types were used for post-classification labeling. They are

- WATER
- HIGH DENSITY MIXED RESIDENTIAL/COMMERCIAL LAND
- LOW DENSITY HIGH CLASS RESIDENTIAL LAND
- PUBLIC HOUSING ESTATES
- INDUSTRIAL LAND
- OPEN SPACE
- GRASS
- WOODLAND AND SCRUBLAND
- CONIFEROUS WOODLAND
- WOODLAND ON SHADOWED SLOPES

Five post-classified images were produced based on 3 by 3, 5 by 5, 7 by 7, 9 by 9, and 11 by 11 window sizes. Figure 7 illustrates the post-classified image using a window size of 7 by 7. Table 2 illustrates the overall accuracies and Kappa coefficients of agreement of the classifications.

Results and Discussion

Unsupervised Classification Result

The unsupervised classified image (Figure 3) generated with eight spectral classes has an overall accuracy of 84.4 percent and a Kappa coefficient of 81.9. Spectral classes are intermingled together due to the complexity of LU/LC in the study area. In heterogeneous LU/LC areas such as HIGH DENSITY

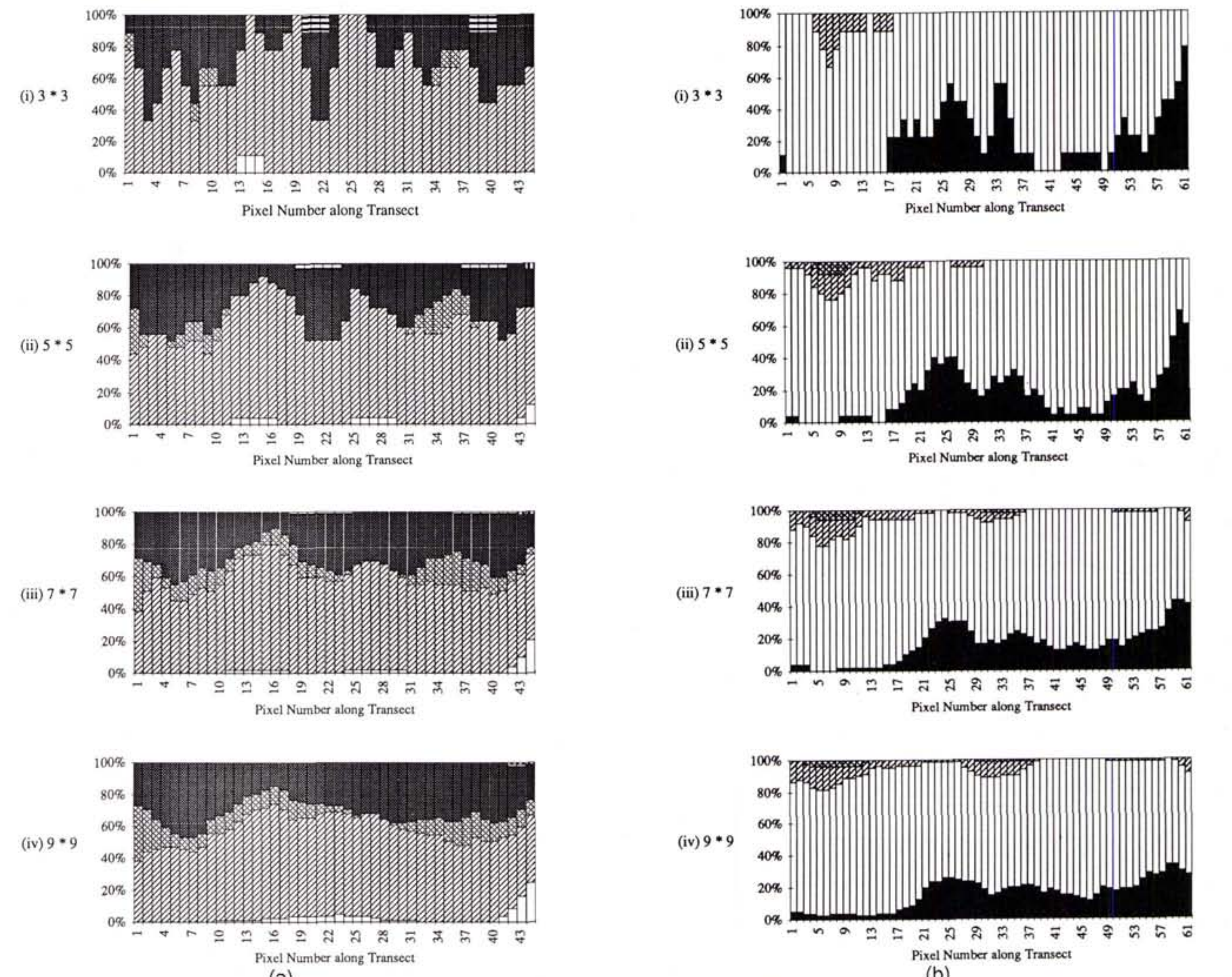

Figure 5. (a) Transects showing the variation of SCSC of LOW DENSITY HIGH CLASS RESIDENTIAL LAND with window sizes ranging from 3 by 3 to 9 by 9 (refer to Figure 4 for legend). (b) Transects showing the variation of SCSC of HIGH DENSITY MIXED RESIDENTIAL AND COMMERCIAL LAND with window sizes ranging from 3 by 3 to 9 by 9 (refer to Figure 4 for legend).

MIXED RESIDENTAL/COMMERCIAL LAND, a mixture of high density urban land, low density urban land, and water is found. Water appears in this LU/LC as it resembles the reflectance values of building shadow. This problem is related to spectral confusion and is difficult to solve based on per-pixel classification alone. As spectral classes are land-cover based, urban LU/LC types with similar ground features are difficult to differentiate. It is only possible to categorize the spectral classes as high density urban land and low density urban land only. This again illustrates a pitfall of the land-cover-based per-pixel classification.

SCSC of Test Sites

Figure 4 illustrates that most test sites are characterized with a certain degree of spectral heterogeneity. Highly complex LU/LC types such as HIGH DENSITY MIXED RESIDENTIAL AND COMMERCIAL LAND in Mongkok (Site No. 7) comprises 15.8 percent of water, 75.9 percent of high density urban land, 7.7 percent of low density urban land, and 0.5 percent of open space. Clearly, this LU/LC type is dominated by the most likely spectral class, i.e., high density urban land. The appearance of water is largely associated with the building shadows while spectral classes of low density urban land and open space are related to road networks in this area.

In contrast, LOW DENSITY HIGH CLASS RESIDENTIAL LAND (Site No. 5) is composed of 5.1 percent of high density urban land, 64.4 percent of low density urban land, 6.9 percent of open space, 23.2 percent of grass, and 0.5 percent of coniferous woodland. Similarly, this LU/LC is dominated by the most likely spectral class, i.e., low density urban land. The high proportion of vegetation spectral classes (over 20 percent) forms a very distinctive contrast with other urban LU/LC types in the study area. A low building height also characterizes this LU/LC as the spectral class of water is not included.

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if ( pV = 0. ) then
        if ( p1 > 0.7 )                              LU/LC ∈ WATER
        if ( p1 < 0.4 ) and ( p2 > 0.4 )             LU/LC ∈ MIXED RESIDENTIAL/COMMERCIAL LAND
        if ( 0.4 < p3 < 0.8 ) and ( p4 < 0.7 )       LU/LC ∈ INDUSTRIAL LAND
        if ( p4 > 0.7 )                              LU/LC ∈ OPEN SPACE

else if ( 0. < pV < 0.5 ) then
        if ( p3 > 2 * p2 )                           LU/LC ∈ HIGH CLASS RESIDENTIAL LAND
        if ( p4 < 0.7 ) and ( p5 < 0.3 )             LU/LC ∈ PUBLIC HOUSING ESTATES

else if ( pV > 0.5 ) then
        if ( p5 > 0.5 )                              LU/LC ∈ GRASS
        if ( p6 > 0.6 ) and ( p7 < 0.3 )             LU/LC ∈ WOODLAND AND SCRUBLAND
        if ( p7 > 0.7 )                              LU/LC ∈ CONIFEROUS WOODLAND
        if ( p8 > 0.5 )                              LU/LC ∈ WOODLAND ON SHADOWED SLOPE

where

p1 = proportion of water
p2 = proportion of high density urban land
p3 = proportion of low density urban land
p4 = proportion of open space/bare soil
p5 = proportion of grass
p6 = proportion of woodland and scrub
p7 = proportion of coniferous woodland
p8 = proportion of woodland shadow
pV = proportion of vegetation = p5 + p6 + p7 + p8
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Figure 6. Decision rules for post-classification labeling with a window size of 7 by 7.

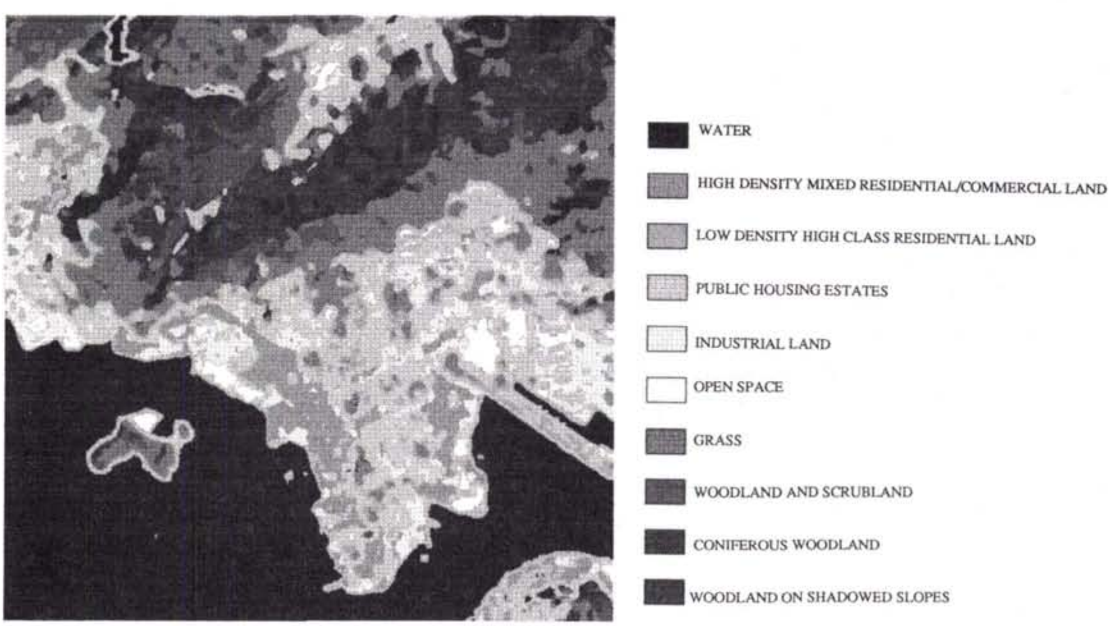

Figure 7. Post-classification labeled image based on ranges of SCSC with a window size of 7 by 7.

For INDUSTRIAL LAND, Site No. 12 consists of newly developed industrial estates with large building blocks and little vegetation. Its composition includes 0.8 percent of water, 16.9 percent of high density urban land, 47.3 percent of low density urban land, 33.2 percent of open space, and 1.8 percent of grass. No spectral class predominates but the high proportions of low density urban land and open space spectral classes make it distinctive from other LU/LC types.

On the other hand, some LU/LC types do exhibit a high degree of homogeneity. For instance, Site Nos. 1 and 2 are two test sites of WATER which are composed of over 99 percent of water.

TABLE 2. ACCURACY OF POST-CLASSIFICATION LABELED IMAGES

Classification Methods	Overall Accuracy (%)	Kappa Coefficient
Spectral Composition (3 by 3)	69.8	66.9
Spectral Composition (5 by 5)	73.1	70.4
Spectral Composition (7 by 7)	74.8	72.2
Spectral Composition (9 by 9)	73.7	71.0
Spectral Composition (11 by 11)	72.0	69.0

Clearly, the degree of heterogeneity varies significantly among different LU/LC types. Also, different LU/LC types do possess unique SCSC. This structural information can be a valuable source of information for further analysis. However, it is important to determine whether SCSC varies significantly within a particular LU/LC type. The variation of SCSC is thus examined.

Variation of SCSC

SCSC may vary in different parts of an LU/LC type. An analysis of selected transects reveals the variability of SCSC. For instance, the proportion of low density urban land in LOW DENSITY HIGH CLASS RESIDENTIAL LAND ranges from 44 percent to 88 percent with a window size of 5 by 5 (Figures 5a). Other spectral classes also vary with different proportional ranges. It is found that overall SCSC extracted from the entire test sites tends to fall within ranges of SCSC derived from moving windows along selected transects. There is no clear distinction between SCSC at the center and those at the boundary.

With a small window size of 3 by 3, changes in SCSC along the transect tend to be relatively abrupt. There are individual pixels with their surrounding eight pixels all belonging to the same spectral class, while in other locations along the transect, the composition may drop to less than 40 percent for the same spectral class. With a larger window size, this type of change is rarely found. Variation in SCSC tends to be smoother as more pixels are included. This effect resembles the use of a low pass filter with a large template size which tends to yield a smooth but blurred image.

A small window size also means that a small number of pixels is used to generate the SCSC information. Minor spectral classes may not be included. For instance, for LOW DENSITY HIGH CLASS RESIDENTIAL LAND, grass is not found along any part of the transect when using a 3 by 3 window size (Figure 5a). As a contrast, it is included everywhere along the transect if a large window size is used.

From the two examples, it is also found that, as window size increases, the range of variation in SCSC tends to decrease. The only exception is high density urban land in LOW DENSITY HIGH CLASS RESIDENTIAL LAND. This is found to be related to the inclusion of pixels lying on the boundary of the test site.

In general, a small window size may not be able to capture sufficient data to describe the SCSC. It tends to yield a great variation, which also causes problems in characterizing LU/LC types. In contrast, too large a window size tends to include extra spectral classes. This effect also produces problems because wrong information is generated. To examine which window size is optimal for characterizing the LU/LC types in the study area, the results from post-classification labeling are analyzed.

Post-Classification Labeling Results

On the whole, the post-classification labeling process tends to generalize the classification result (Figure 7). The larger the window size, the greater the level of generalization. Boundaries between LU/LC types become clearer. However, too large a window size tends to overgeneralize, leading to a loss of details, particularly the shape of LU/LC areas.

LU/LC types with similar ground features can be characterized based on the composition of these features. For instance, identification of INDUSTRIAL LAND based on per-pixel classification of raw radiance values is difficult due to its spectral similarity with other urban LU/LC types. Using SCSC, one is able to locate the major industrial areas in Hong Kong.

The overall accuracies using ten LU/LC types range from 69.8 to 74.8 percent. Error is mainly found among the urban LU/LC types. Most PUBLIC HOUSING ESTATES are identified as LOW DENSITY HIGH CLASS RESIDENTIAL LAND. Along the boundary between WOODLAND and WATER, misclassification occurs because in the original unsupervised classification mixed pixels of land and water were classified as low density urban land or high density urban land. This error propagates in the post-classification labeling process resulting in an erroneous ring of LOW DENSITY HIGH CLASS RESIDENTIAL LAND surrounding a reservior (WATER) and an island covered with WOODLAND AND SCRUBLAND.

The most accurate image was produced from classification with a window size of 7 by 7. Overall accuracy decreases with a decreasing or increasing window size. This result suggests that a window size of 7 by 7 is most appropriate in describing the spectral heterogeneity of LU/LC types in Hong Kong at Level-II classification. It also confirms the results derived from the analysis of variation of SCSC using various window sizes. A small window size is not able to fully describe the heterogeneity of SCSC whereas too large a window size tends to incorporate features located outside the LU/LC type. A poorer result is thus produced.

Conclusion

With the use of high spatial resolution data, spectral heterogeneity poses serious limitations to conventional per-pixel based techniques. The concept of SCSC proposes to use spatial and structural data for image analysis. The results indicated that SCSC can provide a useful information in the study of structural composition of heterogeneous LU/LC. Its main advantage is that different LU/LC types possess different SCSC. This information assists in identifying LU/LC types which are heterogeneous and whose spectral properties are similar. Its disadvantage is that it is in essence a generalization process. The output from post-classification labeling is generalized and loses the details in shape.

Further research should focus on the number of spectral classes used to typify the LU/LC categories. In this paper, the original number (40) of spectral classes was generalized into eight classes. Intuitively, they can be further generalized into three classes of water, bare soil, and vegetation. Would this be sufficient to characterize different LU/LC types? Using a larger number of spectral classes may provide more details, but at the expense of being trivial as many spectral classes may only occupy a small proportion.

It should be noted that SCSC as proportional data is in fact imprecise and inexact. As shown in the analysis, proportion of SCSC may vary significantly within LU/LC types. The range is used because it is the most convenient means to characterize the LU/LC types. With an inexact proportion, these data are also suitable for applying fuzzy set theory to define the LU/LC types and to classify them. A better classification result may perhaps be attained.

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(Received 13 April 1992; revised and accepted 15 December 1992; revised 13 January 1993)