A sub-pixel analysis of urbanization effect on land surface temperature and its interplay with impervious surface and vegetation coverage in Indianapolis, United States

Qihao Weng a,*, Dengsheng Lu b,1

a Department of Geography, Geology, and Anthropology, Indiana State University, Terre Haute, IN 47809, USA
b Center for the Study of Institutions, Population, and Environmental Change, Indiana University, Bloomington, IN 47408, USA

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Abstract

This study developed an analytical procedure based upon a spectral unmixing model for characterizing and quantifying urban landscape changes in Indianapolis, Indiana, the United States, and for examining the environmental impact of such changes on land surface temperatures (LST). Three dates of Landsat TM/ETM+ images, acquired in 1991, 1995, and 2000, respectively, were utilized to document the historical morphological changes in impervious surface and vegetation coverage and to analyze the relationship between these changes and those occurred in LST. Three fraction endmembers, i.e., impervious surface, green vegetation, and shade, were derived with an unconstrained least-squares solution. A hybrid classification procedure, which combined maximum-likelihood and decision-tree algorithms, was developed to classify the fraction images into land use and land cover classes. Correlation analyses were conducted to investigate the changing relationships of LST with impervious surface and vegetation coverage. Results indicate that multi-temporal fraction images were effective for quantifying the dynamics of urban morphology and for deriving a reliable measurement of environmental variables such as vegetation abundance and impervious surface coverage. Urbanization created an evolved inverse relationship between impervious and vegetation coverage, and brought about new LST patterns because of LST’s correlations with both impervious and vegetation coverage. Further researches should be directed to refine spectral mixture modeling by stratification, and by the use of multiple endmembers and hyperspectral imagery. © 2007 Elsevier B.V. All rights reserved.

Keywords: Spectral mixture analysis; Urban land cover; Land surface temperature; Impervious surface; Vegetation abundance; Indianapolis

1. Introduction

In the process of urban development, the partitioning of incoming solar radiation into fluxes of sensible and latent heat is skewed in favor of increased sensible heat flux, as evapotranspirative surfaces are reduced. A higher level of latent heat exchange was found with more vegetated areas, while sensible heat exchange was more favored by sparsely vegetated such as urban impervious areas (Oke, 1982). Research on land surface temperature (LST) shows that this partitioning of heat fluxes and thus surface energy response is a function of varying surface soil water content and vegetation cover (Owen et al., 1998). For non-vegetated areas, LST measurements typically represent the radiometric temperatures of sunlit non-vegetated surfaces, such as bare soil. As the amount of vegetation cover increases,
the radiative temperature recorded by a sensor approximates more closely the temperatures of green leaves, and the canopy temperature at spectral vegetation maximum or complete canopy cover (Goward et al., 2002). Because of its significance, recent remote-sensing literature has witnessed a growing interest in the relationship between LST and vegetation abundance (e.g., Carson et al., 1994; Gallo and Owen, 1998; Gillies and Carlson, 1995; Gillies et al., 1997; Lo et al., 1997; Goward et al., 2002; Weng, 2001; Weng et al., 2004).

The reception and loss of radiation of urban surfaces correspond closely to the distribution of land use and land cover (LULC) characteristics. Each component surface in urban landscapes (e.g., lawn, parking lot, road, building, cemetery, and garden) exhibits a unique radiative, thermal, moisture, and aerodynamic properties, and relates to their surrounding site environment (Oke, 1982). The myriad of the component surfaces and the spatial complexity when they mosaicked create a limitless array of surface energy balance and micro-climate systems (Oke, 1982). These component surfaces are typically smaller than the spatial resolution of some widely used sensors such as Landsat Thematic Mapper (TM) or Enhanced Thematic Mapper Plus (ETM+) images (with a nominal 30-m spatial resolution). As the spatial resolution interacts with the fabric of urban landscapes, a special problem of mixed pixels is created, where several LULC types are contained in one pixel. Mixed pixels have been recognized as a major problem affecting the effective use of remotely sensed data in urban LULC classification and change detection (Fisher, 1997; Cracknell, 1998). Traditional classifiers are per-pixel based, and cannot effectively handle the mixed pixel problem. Use of high spatial resolution image data does not lead to high accuracy of classification due to some new problems associated with these data, notably shades caused by topography, tall buildings, or trees, and high spectral variation within the same land cover class. Likewise, satellite detection of LST and urban heat islands (UHI) based on these measurements encounter the problem of composite signatures, which are created when pure spectral responses of specific features are confused with the pure responses of other features in a pixel.

Because of the correspondence between urban thermal behavior and LULC, over the past decade, there was a tendency to use thematic LULC data, not quantitative surface descriptors, to describe urban thermal landscapes. This trend of qualitative description of thermal patterns and simple correlations between LULC types and their thermal signatures has slowed down the development of remote-sensing of LST and thus surface temperature heat islands (Voogt and Oke, 2003). Clapham (2003) suggests that per-pixel based classification of satellite imagery loses both spatial resolution and statistical information, and advocates the use of continuum-based classification, which aims to provide continuous data for the “functional classes”. The idea of a continuum-based classification has been previously pursued in urban landscape analysis. One of the major advances is Ridd (1995) vegetation–impervious surface–soil (V–I–S) model for characterizing biophysical composition of urban environments. The V–I–S model assumes that urban land covers may be a linear combination of three components: vegetation, impervious surface, and soil, and provides the potential for a link of these components with remote-sensing spectral characteristics. Ridd (1995) suggest that this model may be applied to spatial–temporal analyses of urban morphology, biophysical, and human systems. Recently, this conceptual model has been successfully implemented by using the technique of spectral mixture analysis (SMA). Ward et al. (2000) applied a hierarchical unsupervised classification approach to a TM image in southeast Queensland, Australia, based on the V–I–S model. An adjusted overall accuracy of 83% was achieved. Madhavan et al. (2001) used an unsupervised classifier to classify TM images in Bangkok, Thailand, and the V–I–S model was found to be useful for improving classification. Phinn et al. (2002) compared traditional image classification and aerial photographs interpretation with a constrained linear SMA, and found that the V–I–S fraction images derived from SMA of a TM image in southeast Queensland, Australia provided a better classification result than per-pixel classification and aggregated aerialphotograph interpretation. Wu and Murray (2003) used SMA to analyze impervious surface distribution in Columbus, Ohio, USA, and found that impervious surface can be estimated using a linear regression model of low and high albedo endmember fractions.

It becomes clear that the relationship between LST and land cover characteristics should be examined at the sub-pixel scale. No research attempt has been made to use the V–I–S model for an examination of the environmental impacts of urbanization, as advocated by Ridd (1995). In this paper, multi-temporal Landsat TM/ETM+ imagery of 1991, 1995, and 2000 were used to investigate the effect of urban development on LST and its interplay with impervious surface and vegetation coverage in the City of Indianapolis, Indiana, U.S.A. Specific objectives of this research are: (1) to apply linear SMA to characterize the changing patterns of the urban landscape; (2) to analyze spatial–temporal
variations of UHI using LST measurements derived from Landsat thermal infrared data; (3) to examine changes in the relationship between LST and SMA-derived impervious surface and vegetation coverage as a result of continued urbanization. In so doing, we expect to gain new insights into urban thermal dynamics.

2. The study area

The city of Indianapolis, located in Marion County, Indiana, with a population of over 800,000, was chosen as the study area (Fig. 1). It is a key center of manufacturing, warehousing, distribution, and transportation. Situated in the middle of the country, Indianapolis possesses several other advantages that make it an appropriate choice. It has a single central city, and other large urban areas in the vicinity have not influenced its growth. The city is located on a flat plain, and is relatively symmetrical, having possibilities of expansion in all directions. Like most American cities, Indianapolis is increasing in population and in area. The areal expansion is through encroachment into the adjacent agricultural and non-urban land. Certain decision-making forces, such as density of population, distance to work, property value, and income structure, encourage some sectors of metropolitan Indianapolis to expand faster than others. Examining the environmental impacts of urban expansion in Indianapolis is conducive to understanding and planning its future development, and is especially useful for evaluating the need for new or revised urban design and landscaping policies for mitigating the adverse thermal effects of building geometry, building mass, and poor landscape layouts.

3. Methods

3.1. Image pre-processing

Landsat TM images of June 6, 1991 (acquisition time: approximately 10:45 a.m.) and July 3, 1995 (approximately 10:28 a.m.), and a Landsat ETM+ image of June 22, 2000 (approximately 11:14 a.m.) were selected for use in this study based on the consideration of vegetation phenology and availability of good quality images. Although the images purchased were geometrically corrected, its geometrical accuracy was not high enough for combining them with other high-resolution data sets. The images were therefore further rectified to a common Universal Transverse Mercator coordinate system based on 1:24,000 scale topographic maps, and were resampled to a pixel size of 30 m for all bands using the nearest-neighbor algorithm. A root mean square error of less than 0.5 pixels was obtained for all the rectifications. The Landsat images were all acquired under clear sky conditions. An improved image-based dark object subtraction model was applied to implement atmospheric correction for the images (Lu et al., 2002).

3.2. Linear spectral unmixing

LSMA is a physically based image processing method. It assumes that the spectrum measured by a
sensor is a linear combination of the spectra of all components within the pixel (Adams et al., 1995; Roberts et al., 1998a). The mathematical model of LSMA can be expressed as:

\[ R_i = \sum_{k=1}^{n} f_k R_{ik} + ER_i \]  

(1)

where \( i = 1, \ldots, m \) (number of spectral bands); \( k = 1, \ldots, n \) (number of endmembers); \( R_i \) the spectral reflectance of band \( i \) of a pixel which contains one or more endmembers; \( f_k \) the proportion of endmember \( k \) within the pixel; \( R_{ik} \) the known spectral reflectance of endmember \( k \) within the pixel on band \( i \); \( ER_i \) is the error for band \( i \). To solve \( f_k \), the following conditions must be satisfied: (1) selected endmembers should be independent of each other, (2) the number of endmembers should be less than or equal to the spectral bands used, and (3) selected spectral bands should not be highly correlated.

Estimation of endmember fraction images with LSMA involves image processing, endmember selection, and unmixing solution and evaluation of fraction images. Of these steps, selecting suitable endmembers is the most critical one in the development of high quality fraction images. Following georectification, the minimum noise fraction (MNF) transformation (Green et al., 1988) was performed to reduce data redundancy and correlations between spectral bands (bands 1–5 and 7). The first four components were retained for use in the LSMA models, while the last two components discarded due to the high proportion of noise content.

3.3. Endmember selection

Endmembers were initially identified from the TM/ETM+ images based on high-resolution aerial photographs. Four types of endmembers were selected: shade, green vegetation (GV), impervious surfaces (such as building roofs and roads), and soils (including dry soil and dark soil). The shade endmember was identified from the areas of clear and deep water, while GV was selected from the areas of dense grass and cover crops. Different types of impervious surfaces were selected from building roofs, airport runway, and highway intersections. Soils were selected from bare grounds in agricultural lands. Next, these initial endmembers were compared with those endmembers selected from the scatterplots of MNF1 and MNF2, and of MNF1 and MNF3. The endmembers with similar MNF spectra located at the extreme vertices of the scatterplots were selected. These endmembers were shade, GV, impervious surface, dry soil, and dark soil. An unconstrained least-squares regression solution was used to unmix the MNF components into fraction images.

To find the best quality of fraction images, different combinations of endmembers were tested. The combinations were: (1) four endmembers with shade, GV, impervious surface, and dark soil; (2) three endmembers with shade, GV, and impervious surface; (3) three endmembers with shade, GV, and dry soil; (4) three endmembers with shade, GV, and dark soil. Visualization of fraction images, analysis of fraction characteristics of representative land cover types, and assessment of error images were conducted to determine which combination provided the best fractions for the study area. Because this study is more interested in characterizing urban LULC patterns than non-urban regions, the criteria for selecting the most suitable fraction images are based on (1) high-quality fraction images for urban areas, (2) relatively low errors, and (3) the distinction among typical LULC types. Results indicated that a three-endmember combination of shade–GV–impervious surface provided a satisfactory result for the study area. Fraction images derived from these three endmembers were further used for classification, and will be examined later.

3.4. Image classification

High-spatial resolution aerial photographs were used to identify LULC sample plots, which covered 10 LULC types: commercial and industrial, high-density residential, low-density residential, bare soil, crop, grass, pasture, forest, wetland, and water. On average, 10–16 sample plots for each class were selected. A window size of 3 × 3 was applied to extract the fraction value for each plot. The average value and standard deviation were then calculated for each LULC class.

The maximum-likelihood classification (MLC) algorithm was applied to classify the fraction images into 10 classes, generating a classified image and a distance image. A distance threshold was selected for each class to screen out potential confusing pixels, and was determined by examining interactively the histogram of each class in the distance image. Pixels with a distance value greater than the threshold were assigned a class value of zero in the thematic image.

The MLC is a parametric classifier that assumes normal or near normal spectral distribution for each feature of interest, associated with an equal prior probability among the classes. Hence, training samples insufficient in number or non-representative of features
of interest or having multimodal distributions often lead to poor classification results because of inaccurate estimation of the mean vector and covariance matrix used in the MLC algorithm. Under these circumstances, a non-parametric classifier, such as the distance tree classifier (DTC), would be more suitable to use because no assumption of data distribution is required. Therefore, the DTC approach was applied in this study to reclassify the pixels that were set to zero based on the distance image. The thresholds required by DTC were identified based on the mean and standard deviation from the sample plots for each class.

In urban landscape analysis, land use data are often more useful than land cover data because of their pertinence to planning and environmental management issues. Further derivation of land use data from a classified land cover image is often desirable. Having considered LULC characteristics and applications of the study area, the classified LULC image was finally merged into six classes: commercial and industrial, residential, pasture and agricultural land, grassland, forest, and water. Pasture and cropland were combined because of their highly similar spectral responses and fractions. Wetland was very limited in extent, and was therefore merged into either forest or water depending on their spectral characteristics. When grassland was found to be confused with pasture or cropland in urban or residential areas, these pasture or cropland would be merged with grassland; whereas in the agricultural areas, they were merged into pasture–agricultural lands.

3.5. Accuracy assessment of classified images

The accuracy of the classified images was checked with a stratified random sampling method using 150 samples. The reference data were collected from large-scale aerial photographs. Overall accuracy, producer’s accuracy, and user’s accuracy were calculated based on the error matrix for each classified map, as well as the KHAT statistic, kappa variance, and Z statistic. The overall accuracy of LULC map for 1991, 1995, and 2000 were determined to be 90, 88, and 89%, respectively. Clearly, LULC data derived from the SMA procedure have reasonably high accuracy, and are sufficient for urban landscape analysis and change detection. The main misclassifications arise from: (1) roads within urban and residential areas where some roads were classified as urban areas and others as residential depending on the road width and associated environmental conditions along the roads, (2) confusion between urban and dry bare soils in pasture and agricultural areas, and (3) confusion among grass, pasture, and some crops. Taken the 2000 ETM+ image as an example, a comparison of SMA-based image classification performance with MLC of all multi-spectral bands of the same image was conducted. Table 1 shows the error matrices for the two classified images. A significant improvement was found with the SMA-based image classification method (overall accuracy: 89% versus 80%). The kappa coefficients for the two maps were 0.86 and 0.73, respectively.

<table>
<thead>
<tr>
<th>Method</th>
<th>Classified data</th>
<th>Reference data</th>
<th>Ref. totals</th>
<th>Class. totals</th>
<th>Number correct</th>
<th>PA (%)</th>
<th>UA (%)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Urban</td>
<td>Res.</td>
<td>Forest</td>
<td>Grass</td>
<td>PS-AG</td>
<td>Water</td>
<td></td>
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<td>28</td>
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<td>0</td>
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<td></td>
<td>PS-AG</td>
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<td>0</td>
<td>1</td>
<td>3</td>
<td>16</td>
<td>0</td>
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<tr>
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<td>0</td>
<td>4</td>
<td>0</td>
<td>4</td>
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<tr>
<td>Overall classification accuracy = 89.33% (i.e., 120/150), overall kappa statistics = 0.8575</td>
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<th>Method</th>
<th>Classified data</th>
<th>Reference data</th>
<th>Ref. totals</th>
<th>Class. totals</th>
<th>Number correct</th>
<th>PA (%)</th>
<th>UA (%)</th>
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</thead>
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<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
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<tr>
<td></td>
<td>Residential</td>
<td>7</td>
<td>56</td>
<td>0</td>
<td>7</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Forest</td>
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<td>0</td>
<td>8</td>
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<tr>
<td></td>
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<td>3</td>
<td>18</td>
<td>2</td>
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<tr>
<td></td>
<td>PS-AG</td>
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<td>0</td>
<td>0</td>
<td>7</td>
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<tr>
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<td>0</td>
<td>0</td>
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<td>4</td>
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<tr>
<td>Overall classification accuracy = 80.00% (i.e., 120/150), overall kappa statistics = 0.7284</td>
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Note: Variance for SMA = 0.001115; variance for MLC = 0.001923; Z statistics = 2.342654; significant at 98% confidence level. Ref.: reference; Class.: classified; PA and UA: producer’s accuracy and user’s accuracy, respectively.

a Res.: residential.
b PS-AG: pasture and agricultural lands.
3.6. Derivation of LST

LST were derived from geometrically corrected TM/ETM+ TIR band (10.44–12.42 μm). The TM thermal band has a spatial resolution of 120 m and a noise level equivalent to a temperature difference of 0.5 °C (Gibbons and Wukelic, 1989). The ETM+ thermal band has a spatial resolution of 60 m. The thermal imagery from Landsat 7 is generally well calibrated to ground truth data (Arvidson, 2002). The local time of satellite overpasses were in the morning (approximately 10:30–11 00 a.m.), so that the chance for detecting a weak UHI is maximized.

The following equation was used to convert the digital number (DN) of Landsat TM TIR band into spectral radiance (Markham and Barker, 1985):

\[ L_\lambda = 0.0056322 \times DN + 0.1238 \]  
(2)

The equation to convert the digital number of Landsat ETM+ TIR band into spectral radiance is (Landsat Project Science Office, 2002):

\[ L_\lambda = 0.0370588 \times DN + 3.2 \]  
(3)

The next step is to convert the spectral radiance to at-satellite brightness temperature (i.e., blackbody temperature, \( T_B \)) under the assumption of uniform emissivity (Wukelic et al., 1989; Landsat Project Science Office, 2002). The conversion formula is:

\[ T_B = \frac{K_2}{\ln((K_1/L_\lambda) + 1)} \]  
(4)

where \( T_B \) is the effective at-satellite temperature in Kelvin (K), \( L_\lambda \) the spectral radiance in W m\(^{-2}\) sr\(^{-1}\) μm\(^{-1}\); \( K_2 \) and \( K_1 \) are the pre-launch calibration constants. For Landsat-5 TM images, \( K_2 = 1260.56 \) K, and \( K_1 = 60.776 \) mW cm\(^{-2}\) sr\(^{-1}\) μm\(^{-1}\). For Landsat-7 ETM+ images, \( K_2 = 1282.71 \) K, and \( K_1 = 666.09 \) mW cm\(^{-2}\) sr\(^{-1}\) μm\(^{-1}\).

The temperature values obtained above are referenced to a black body. Therefore, corrections for spectral emissivity (\( \varepsilon \)) became necessary according to the nature of land cover. Each of the LULC categories was assigned an emissivity value by reference to the emissivity classification scheme by Snyder et al. (1998). The emissivity corrected land surface temperatures (LST) were computed as follows (Artis and Carnahan, 1982):

\[ \text{LST} = \frac{T_B}{1 + (\lambda \times T_B/\rho) \ln \varepsilon} \]  
(5)

where \( \lambda \) is the wavelength of emitted radiance (for which the peak response and the average of the limiting wavelengths (\( \lambda = 11.5 \) μm) (Markham and Barker, 1985) will be used),

\[ \rho = \frac{h \times c}{\sigma} (1.438 \times 10^{-2} \) mK),

\( \sigma \) is the Boltzmann constant (1.38 \times 10^{-23} J/K), \( h \) the Planck’s constant (6.626 \times 10^{-34} J s), and \( c \) is the velocity of light (2.998 \times 10^8 m/s).

3.7. Identification of UHIs

The UHI patterns were identified using the following procedures, which combines the methods developed by Weng (2001) and DeWitt and Brennan (2001). For each LST map, a base temperature was calculated by averaging the thermal signatures of non-urban land cover types (i.e., forest, water, grassland, and pasture and agriculture) in the rural area of the city. Next, LST values were classified into a temperature zone map based on the percent increase of each temperature value above the given base temperature. Five temperature zones were identified, including a base temperature zone, zones of up to 2% temperature increase, up to 4%, up to 6%, and 6% and above. This identification based on relative temperature differences allows an examination of the locations and areal extent of UHIs. Moreover, by using an image-differencing technique between two temperature zone maps, the development of UHI over the time can be studied. The pattern of UHI changes can be better understood by GIS analysis through overlaying the UHI maps with those of impervious surface and vegetation fraction.

4. Results and analysis

4.1. Urban development and changes in impervious surface

Pixel values of a fraction image represent the areal proportions of each endmember within a pixel. Fig. 2 shows fraction images – shade, GV, and impervious surface – in the 3 years. In the shade fraction images, water appeared very bright due to its high shade fraction. This is because shade endmember was selected from clear and deep water, assuming that shade had similar spectral characteristics with water. Commercial/industrial land, residential land, and forest had medium shade fraction values as indicated by their grey tone. Grassland, pasture, and agricultural lands had a dark tone, indicative of the lowest fraction of shade. In the GV fraction images, forest and dense grassland/pasture appeared very bright, while residential areas and crops
appeared grey. Commercial/industrial land, bare soils, and water had a dark tone. The progression from areas of low to high GV fraction was apparent in the transition from high-density urban areas with minimal vegetation cover to low-density urban areas with a large proportion of vegetation cover. In the impervious fraction images, the transition from commercial/industrial land to high residential to low residential land was consistent with the tonal change from white to bright grey to dark grey. Forest, water, and areas of dense grassland/pasture exhibited a dark tone in the impervious fraction images.

Three dates of fraction images were classified into three thematic maps. Fig. 3 shows the classified maps. Table 2 shows the composition of LULC by year and changes occurred between 1991 and 2000. In 1991, residential use and pasture–agriculture accounted equally for 27% of the total land, while grassland shared another 20%. The combination of commercial and industrial land used 13% of the total area, and forestland had a close match, yielding another 10%. Water bodies occupied the remaining 3%, and this percentage kept unchanged from 1991 to 2000. However, LULC dynamics occurred in all other categories, as seen in Fig. 4 and Table 2. The most notable increment was observed in residential use, which grew from 27% in 1991, to 33% in 1995, leveling out in 2000 to 38%. Associated with this change, grassland was increased from 20 to 23%. Highly developed land, mainly for commercial, industrial uses, transportation, and utilizes, continued to expand.
In 2000, it accounted for over 15,000 ha, or 15%, generating a 2% of increase over the 9 years. These results suggest that urban land dispersal in Indianapolis was more related to urban population increase than to economic growth during the study period. In contrast, a pronounced decrease in pasture and agricultural land was discovered from 1991 (27%) to 1995 (20%). This decrease was also evident between 1995 and 2000, when pasture and agricultural land was further shrunk by 6581.30 ha (31.56%). Forestland in a city like Indianapolis was understandably limited in size. Our remote-sensing GIS analysis indicates, however, that forestland continued to disappear with a stable marked rate. Between 1991 and 2000, forestland was reduced by 2864.81 ha (i.e., 28.75%) and leveled down to approximately 7100 ha. The cross-tabulation of the 1991 and 2000 LULC maps reveals that most of the losses in pasture, agricultural and forestland were converted to residential and other urban uses, owing to the process of urbanization and sub-urbanization. GIS overlay of the two maps further shows the spatial occurrence of urban expansion to be mostly in the edges of the city. It is worth noting that commercial and industrial use in 1995 appeared anomaly high due to its

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<tbody>
<tr>
<td>Commercial and industrial</td>
<td>3384.40 (25.40%)</td>
<td>−1217.50 (−7.29%)</td>
<td>2,166.90 (16.27%)</td>
</tr>
<tr>
<td>Residential</td>
<td>5414.80 (18.86%)</td>
<td>6648 (19.48%)</td>
<td>12,062.80 (42.02%)</td>
</tr>
<tr>
<td>Grassland</td>
<td>224,10 (1.06%)</td>
<td>2619.80 (12.27%)</td>
<td>2,843.90 (13.46%)</td>
</tr>
<tr>
<td>Pasture and agriculture</td>
<td>−7612.20 (−26.74%)</td>
<td>−6581.30 (−31.56%)</td>
<td>−14,193.50 (−49.86%)</td>
</tr>
<tr>
<td>Forest</td>
<td>−1417.87 (−14.23%)</td>
<td>−1446.94 (−16.93%)</td>
<td>−2,864.81 (−28.75%)</td>
</tr>
<tr>
<td>Water</td>
<td>9.75 (0.34%)</td>
<td>−0.90 (−0.03%)</td>
<td>8.85 (0.31%)</td>
</tr>
</tbody>
</table>
confusion with dry bare soils in agricultural land and pasture.

These changes in LULC have led to changes in the composition of image fractions. Impervious surface, as an important urban land cover feature, not only indicates the degree of urbanization, but also a major contributor to the environmental impacts of urbanization (Arnold and Gibbons, 1996). The areal extent and spatial occurrence of impervious surfaces significantly influence urban climate by altering sensible and latent heat fluxes within the urban canopy and boundary layers (Yang et al., 2003). To examine how impervious surface in Indianapolis had changed from 1991 to 2000, Fig. 5 was created to show the distribution of impervious coverage for the observed years at four categories. Table 3 shows that the number of pixels with values of greater than zero increased from 42,501 in 1991 to 45,804 in 1995, and further increased to 46,560 in 2000. A comparison between 1991 and 2000 indicates that this increase in pixels took place over the entire range of impervious fraction values (except for the category of 0.1–0.2) (Table 3). This analysis further substantiates the findings that Indianapolis underwent an extensive urbanization process, during which impervious or impenetrable surfaces, such as rooftops, roads, parking lots, driveways, and sidewalks were widely generated. In other words, significant amount of non-urban pixels became urbanized during the study period. Furthermore, in 1991, only 7.03% of the urbanized pixels (pixels that contain some impervious surface areas) had a value of impervious fraction greater than 0.6. In 1995 and 2000, 7.41% and 9.24%, respectively, were observed. This increase of pixel counts in the higher percentage categories of impervious fraction suggests that even more construction could have taken place in previously urbanized pixels, i.e., there existed infill urban growth (Wilson et al., 2003).

4.2. Changes in the UHI patterns

Analysis of the three LST maps that derived from Landsat thermal infrared bands reveals that the extent of UHI in Indianapolis grew substantially between 1991 and 2000. Fig. 6a–c shows the distribution of UHIs in 1991, 1995 and 2000, respectively. It is evident from these maps that there was a thermal gradient as progressed from the Central Business District (CBD) outward into the countryside. Some hot spots, or UHIs (i.e., areas showing higher percentages of temperature range increase above the base temperature), can be easily identified. A notable increase in UHI occurred in the central part of the CBD. The growth was equally evident along Highway 465 (the by-pass of the city shown in Fig. 1), in the north, west, and east side of the city. However, as of 2000, there did not exist an extensive UHI in the southern part of the city, except for a few small ones along southward highways, neither did a pronounced UHI growth from 1991 to 2000. Apparently, forest and agricultural uses in the southern part of the city contained the development of UHIs. Table 4 shows the relative size of each temperature class by year. It is clear from the table that the base temperature zone had dropped approximately by 26%, totaling at 9215.87 ha, while the 2% temperature zone kept basically unchanged. In contrast, the temperature increment zones of up to 4%, up to 6%, and 6% and above expanded in area by 177.40, 779.37, and 230%, respectively. This vast conversion of the base temperature zones to higher temperature range increases (4% and above) zones indicates a growing trend of UHI in the city. The growth was more substantial from 1991 to 1995 than from 1995 to 2000, as reflected in columns 5 and 6 of Table 3.
Previous remote-sensing studies have demonstrated that LULC changes, especially urban development, can alter the patterns and development of UHIs (Lo et al., 1997; Weng, 2001, 2003). Since changes in LULC would lead to changes in the composition of image fractions, the magnitude and spatial distribution of each fraction image should be related to the pattern of UHIs. Correlation analysis (pixel-by-pixel) was conducted between each LST map with GV and impervious surface fraction images of the same year. The significance of each correlation coefficient was determined using a one-tail Student’s t-test. Results indicate that LST was positively correlated with impervious surface fraction, and correlation coefficients were 0.5122 in 1991, 0.5345 in 1995, and 0.5704 in 2000, respectively. In contrast, LST was found to negatively correlate with GV fraction, with a correlation coefficient of −0.5315 in 1991, −0.4103 in 1995, and −0.4629 in 2000. If negative values for each GV and impervious surface fraction were rounded to zero, the associations between LST and the two fractions would become closer. Correlation coefficients between LST and impervious surface would reach 0.5865 in 1991, 0.5775 in 1995, and 0.5789 in 2000, whereas the relationship between LST and GV fraction would improve to a higher level of negative correlation with a coefficient of −0.5610 in 1991, −0.5978 in 1995, and −0.5239 in 2000, respectively. These correlations between LST and GV fraction were found to be significant at the 0.05 level.

Table 4

<table>
<thead>
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</thead>
<tbody>
<tr>
<td>Base temperature</td>
<td>35,335.15</td>
<td>29,751.58</td>
<td>26,119.28</td>
<td>−5583.57 (−15.80%)</td>
<td>−3632.30 (−12.21%)</td>
<td>−9215.87 (−26.08%)</td>
</tr>
<tr>
<td>Up to 2% increase</td>
<td>64,200.97</td>
<td>65,397.90</td>
<td>64,353.51</td>
<td>1196.93 (1.86%)</td>
<td>−1044.39 (−1.60%)</td>
<td>152.54 (0.24%)</td>
</tr>
<tr>
<td>Up to 4% increase</td>
<td>49,411.16</td>
<td>9,234.96</td>
<td>13,706.56</td>
<td>4293.80 (86.90%)</td>
<td>4471.60 (48.42%)</td>
<td>8765.40 (177.40%)</td>
</tr>
<tr>
<td>Up to 6% increase</td>
<td>36.31</td>
<td>124.68</td>
<td>319.30</td>
<td>88.37 (243.38%)</td>
<td>194.62 (154.49%)</td>
<td>282.99 (779.37%)</td>
</tr>
<tr>
<td>Higher than 6% increase</td>
<td>0.65</td>
<td>5.12</td>
<td>15.60</td>
<td>4.47 (687.69%)</td>
<td>10.48 (204.69%)</td>
<td>14.95 (230.00%)</td>
</tr>
</tbody>
</table>

Fig. 5. Distribution of impervious coverage, (a) 1991, (b) 1995, and (c) 2000.
and impervious surface fractions suggest that both vegetation cover and impervious surface contributed to the surface energy balance. As impervious surface is usually inversely related to vegetation cover in urban areas, LST tends to increase as vegetation cover decreases and impervious cover increases in a pixel.

To better understand how the UHI dynamics was related to changes in impervious surface coverage, the UHI analysis results and impervious surface change data were combined for a GIS analysis. Relative temperature changes for the periods of 1991–1995 and 1995–2000 were obtained by performing an image differencing over the UHI temperature classes in the 3 years. The results were regrouped into three relative temperature change zones: increase, unchanged, and decreased. Imperviousness-change data were obtained by subtracting the impervious surface fraction images for the 1991–1995 and 1995–2000 periods and by thresholding the results into three categories: increase, unchanged, and decreased, based on the statistical parameters of data distribution. The GIS analysis indicates that impervious coverage changes were closely related to relative temperature changes. Correlation coefficients were computed to be 0.5296 for 1991–1995 and 0.5790 for 1995–2000, suggesting that temperature increases tended to occur in areas where impervious surface increased. Areas where vegetated cover was lost to imperviousness from one period to the next displayed a corresponding temperature increase.

4.3. Dynamic linkages among LST, impervious surface, and vegetation abundance

In order to have an in-depth understanding of how the dynamics and interplay of impervious surface and vegetation abundance modulate surface energy balance, the statistics of LST, impervious fraction, and vegetation fraction by LULC type were obtained by superimposing LULC image with the images of LST, impervious, and GV fractions in each year. The result

Fig. 6. Maps of UHIs in the observed years, (a) 1991, (b) 1995, and (c) 2000. For each LST map, a base temperature was calculated by averaging the thermal signatures of non-urban land cover types in the rural area of the city. LST values were then classified into five temperature zones based on the percent increase of each temperature value above the base temperature.
of the GIS overlays is shown in Table 5. It is clear that commercial and industrial land exhibited the highest temperature, followed by residential land. The lowest temperature was observed in forest, followed by water bodies. This implies that urban development brought up LST by an average of 6 K by replacing natural environment (forest and water) with commercial, industrial, or residential uses. The standard deviation value of LST was largest for commercial and industrial land, indicating that these surfaces experienced a wide variation in LST because of different construction materials. In contrast, the standard deviation value of LST was relatively small for residential land owing to their homogeneity. Furthermore, residential land possessed a smaller mean value than commercial and industrial land, where buildings were frequently mixed with forest and grassland. Grassland, had an intermediate level of LST, as it owned sparse vegetation and exposed bare soil. Similarly, pasture and agricultural land had an intermediate level of LST. Forests showed a considerably lower LST, because dense vegetation can reduce amount of heat stored in the soil and surface structures through transpiration. All vegetative cover, regardless of natural or man-made, exhibited an extremely small temperature variation. Water tended to get warm slowly during the summer owning to its rather high thermal inertia, and to convection and turbulence (e.g., wave action). Because of distinctive characteristics of rivers, lakes, reservoirs, and ponds, their LST values vary, leading to a large standard deviation value for water.

Three images in the central column of Fig. 2 shows the geographic patterns of vegetation fractions. These images display a large dark area (low values) at the center of the study area corresponding to the CBD of Indianapolis City. Bright areas of high GV values were found in the surrounding areas. Various types of crops were still at the early stage of growth or were before emergence, as indicated by medium grey to dark tone of the GV fraction images in the southeastern and southwestern parts of the city. Table 5 indicates that forest had the highest GV fraction values, followed by grassland. In contrast, commercial and industrial land displayed the lowest GV values. Little vegetative amount was found in water bodies, as indicated by the GV fraction values. Both residential land and pasture-agricultural land yielded an intermediate level of GV fraction value, subject to the impact of the date of image acquired. Residential land generally possessed a bit higher value than pasture and agricultural land. In all of the years observed, however, the latter exhibited the largest standard deviation value, suggesting that pasture

<table>
<thead>
<tr>
<th>Land cover type</th>
<th>1991 TM image</th>
<th>1995 ETM+ image</th>
<th>2000 ETM+ image</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean T_s (standard deviation; K)</td>
<td>Mean impervious surface (standard deviation)</td>
<td>Mean vegetation cover (standard deviation)</td>
<td>Mean impervious surface (standard deviation)</td>
</tr>
<tr>
<td>Commercial and industrial</td>
<td>304.74 (2.83)</td>
<td>0.423 (0.209)</td>
<td>0.087 (0.179)</td>
</tr>
<tr>
<td>Residential</td>
<td>301.09 (1.90)</td>
<td>0.249 (0.077)</td>
<td>0.159 (0.260)</td>
</tr>
<tr>
<td>Grassland</td>
<td>298.01 (1.67)</td>
<td>0.146 (0.088)</td>
<td>0.114 (0.061)</td>
</tr>
<tr>
<td>Pasture and agriculture</td>
<td>299.51 (1.44)</td>
<td>0.252 (0.192)</td>
<td>0.076 (0.090)</td>
</tr>
<tr>
<td>Forest</td>
<td>295.95 (2.10)</td>
<td>0.185 (0.155)</td>
<td>0.049 (0.090)</td>
</tr>
<tr>
<td>Water</td>
<td>297.35 (2.24)</td>
<td>0.276 (0.149)</td>
<td>0.029 (0.090)</td>
</tr>
</tbody>
</table>

and agricultural land may hold various amount of vegetation.

As has been pointed out above, impervious surface is inversely related to vegetation cover in urban areas. In other words, as impervious cover increases within a pixel, vegetation cover would decrease. The percentage of land covered by impervious surfaces varies significantly with LULC categories and sub-categories, which was first observed by the Soil Conservation Service in 1975. The results of this study show a substantially different estimate for each LULC type, as this study applied a spectral unmixing model to the remote-sensing images, and the modeling had introduced some errors. For example, negative impervious fraction values were found in water. Generally speaking, a LULC type with a higher GV fraction appeared to have possession of a lower impervious fraction. The highest impervious coverage was discovered in commercial and industrial land, and was continuously increased over the time. Residential land came in second. A slight increment in the percentage of impervious coverage was also noted from 1991 to 2000. This finding further assure our earlier observation that there were “infill” types of urban development during the study period. Grassland, pasture, and agricultural land detected a lower value of impervious surface, owing largely to their exposed bare soil, confusion with commercial and residential land, and computational errors. Forestland received a minimal impervious fraction value in all years.

The demonstrated relationship between LULC and the three biophysical parameters, LST, GV, and impervious surface fractions, encourages us to investigate the interplay of these environmental variables within each LULC type. A pixel-by-pixel correlation analysis was conducted by computing Pearson’s correlation coefficients between LST, and GV and impervious surface fractions. The resulted Table 6 shows that for all LULC types, LST values were negatively correlated with GV fraction values, but were positively correlated with impervious fraction values. The strongest, negative correlation existed between LST and GV fraction values in agricultural land and pasture and in forest. The correlation coefficient values dropped slightly for residential, and commercial and industrial land, with a sharp decrease for grassland. The least correlation was found in water. In contrast, the highest positive correlation between LST and impervious fraction values was found in agricultural land and pasture, followed by residential land and commercial and industrial land. Grassland exhibited a moderately significant correlation. The lowest correlation was observed in forestland and water.

The above findings suggest that the spatial arrangement and areal extent of different land cover types is a fundamental factor contributing to the variations of spectral radiance and texture in LST and thus to the spatial patterns of UHI. As the sources and sinks for most of the material and energy movements and interactions between the geosphere and biosphere, changes in land covers will not only cause changes in physical quantities such as vegetative abundance and impervious coverage, but also in thermal properties of the surfaces through the interactions among these variables. The dynamic relationship between vegetation and impervious surface coverage creates a unique thermal spectral response for each pixel, and therefore a thermal signature for each LULC type and an aggregated effect on the surface energy balance for the area under investigation. Apparently, land use zoning, as a tool of urban planners, has a profound impact on the physical characteristics of urban landscapes by imposing such restrictions as maximum building height and density, the extent of impervious surface and open space, land use types and activities. These restrictions would impact surface energy exchange, surface and subsurface hydrology, micro- to meso-scale weather and climate systems, and other environmental processes (Wilson et al., 2003).

Table 6

<table>
<thead>
<tr>
<th>Land cover type</th>
<th>1991 TM image</th>
<th>1995 TM image</th>
<th>2000 ETM+ image</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>S/GV fraction</td>
<td>S/impervious surface</td>
<td>S/GV fraction</td>
</tr>
<tr>
<td>Commercial and industrial</td>
<td>−0.63</td>
<td>0.52</td>
<td>−0.63</td>
</tr>
<tr>
<td>Residential</td>
<td>−0.65</td>
<td>0.54</td>
<td>−0.64</td>
</tr>
<tr>
<td>Grassland</td>
<td>−0.43</td>
<td>0.41</td>
<td>−0.35</td>
</tr>
<tr>
<td>Agriculture and pasture</td>
<td>−0.75</td>
<td>0.58</td>
<td>−0.76</td>
</tr>
<tr>
<td>Forest</td>
<td>−0.67</td>
<td>0.29</td>
<td>−0.68</td>
</tr>
<tr>
<td>Water</td>
<td>−0.03</td>
<td>0.37</td>
<td>−0.04</td>
</tr>
</tbody>
</table>
5. Discussion and conclusions

Ridd (1995) suggested that effective use of the V–I–S model provided a possibility for documenting historical morphological changes in vegetation and impervious surface and the impacts of the changes in temperature and other urban environmental variables (p. 2180). To make this documentation a reality, remote-sensing techniques must enable a parsimonious separation of urban LULC types into values directly related to their scale and signature (Phinn et al., 2002). This study has demonstrated that SMA may provide a physically based solution to quantifying spatial and temporal changes in urban landscape compositions, and that SMA-derived fraction estimates may provide a reliable measurement on urban environmental variables such as vegetation abundance and impervious surface coverage. A linkage between these two types of data (i.e., data describing urban morphology and environmental quantities) has made it successful for a sub-pixel analysis of the urbanization effect on LST in Indianapolis, United States.

This study demonstrates that SMA is an effective approach for characterizing urban landscape patterns and for classifying urban LULC. It provides a suitable model to decompose the spectral mixtures of L-resolution data such as Landsat TM/ETM+. Thus, a more realistic representation of the true nature of a surface is possible compared with that provided by the assignment of a single dominant class to every pixel by statistical models. This research indicates that SMA approach is suitable to solve the mixture problem in the L-resolution data and provided better classification results than traditional per-pixel classifiers. Moreover, stable and reliable fraction estimates derived from the multi-temporal image data were found to be more effective for a LULC change detection than traditional pixel-by-pixel comparison methods, because the fractional characteristics of LULC types at one date are comparable with other dates of fraction images.

Fraction images provide a physically based measure of the areal proportions of endmembers within a pixel, which can be easily translated into a deterministic model for significant environmental variables such as impervious surface and vegetation abundance. A previous research has shown that unmixed vegetation fractions provide a stronger negative correlation with LST than a widely used vegetation index, i.e., NDVI, because the areal measure of vegetation abundance within a pixel has a more direct correspondence with the radiative, thermal, and moisture properties of the surface that determine LST (Weng et al., 2004). In addition, unmixed vegetation fractions make use of the full spectral reflectance vector of a sensor, and its values can therefore be easily interpreted and applied (Small, 2001).

This study further reveals that SMA provides a modeling approach for examining the dynamics of environmental impact resulted from urban growth by observing changing fraction constituency over time. At different stages of urban growth, various impacts can be observed. In the early stage of urbanization, removal of trees and vegetation may decrease evapotranspiration. Later, when construction of houses, streets, and culverts initiates, the impacts may include further decreased evapotranspiration, and increased sensible heat flux. After the development of residential and commercial buildings has been completed, increased imperviousness will reduce significantly latent heat flux. This effect of urbanization can be modeled by correlating remotely sensed LST with SMA-derived impervious and vegetation coverage with a time series of remote-sensing data.

Since imperviousness, vegetation abundance, and LST are all land cover related attributes, LST values were unsurprisingly found to be negatively correlated with GV fraction values, but positively correlated with impervious fraction values. Temperature increases occurred in areas where vegetated cover was lost to imperviousness from one period to the next.

SMA, as a remote-sensing-based V–I–S analytical procedure, needs to be refined in order to objectively characterize urban morphology and the environmental consequences. Because of the complexity of impervious surfaces, different urban areas may have substantially various impervious surface types. Identifying a suitable endmember to represent all types of impervious surfaces is often unrealistic. Moreover, impervious surfaces tend to be confused with dry soils. On the other hand, shade is an important component captured by optical remote sensors, which is not included in the V–I–S model. Three possible approaches may be taken to overcome these problems: (1) by stratification, (2) by use of multiple endmembers, and (3) by use of hyperspectral imagery. For a study area with commercial and industrial uses, residential uses, agricultural land, forest and water, identification of suitable endmembers for the whole area is often challenging. More endmembers require more spectral bands to be used, since the maximum number of endmembers is directly proportional to the number of spectral bands plus one. The vastly increased dimensionality of a hyperspectral sensor effectively removes the sensor-related limit on the number of endmembers available. More significantly, the number of hyperspectral image channels far
exceeds the likely number of endmembers for most applications readily permits the exclusion from the analysis of any bands with low signal-to-noise ratios or with significant atmospheric absorption effects (Lillesand et al., 2004, p. 614). In addition, a multiple-endmember SMA approach has shown a better performance than a standard SMA approach, when a large number of endmembers require to be modeled across a scene (Painter et al., 1998; Roberts et al., 1998b; Okin et al., 2001). This approach starts with a series of candidate two-endmember models, and then evaluates each model based on the criteria of fraction values, root mean square error, and residual threshold, and finally produces fraction images with the lowest error (Roberts et al., 1998b).

Acknowledgements

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References


