Modeling Urban Heat Islands and Their Relationship with Impervious Surface and Vegetation Abundance by Using ASTER Images

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Abstract—An important issue in urban thermal remote sensing is how to use pixel-based measurements of land surface temperature (LST) to characterize and quantify the urban heat island (UHI) observed at the meso- and macro-scales. Characterization and modeling of UHIs must consider the inherent spatial non-stationarity within land surface variables. This study extended a kernel convolution modeling method for two-dimensional LST imagery to characterize and model the UHI in Indianapolis, U.S.A., as a Gaussian process. To understand the UHI pattern over the space and time, four ASTER images of different seasons / years were acquired and analyzed. Furthermore, we employed linear spectral mixture analysis to extract sub-pixel urban biophysical variables (i.e., green vegetation/GV and impervious surface/IS), and developed new indices of greenness and imperviousness based on the convoluted indices of GV and IS fractions. These indices were proposed to show the contrast in the urban-rural biophysical environmental conditions. Results indicate that the UHI intensity possessed a stronger correlation with both greenness and imperviousness indices than with GV and IS abundance. Because this study utilized a smoothing kernel to characterize the local variability of urban biophysical parameters including LST, characterized UHIs can therefore be examined as a scale-dependent process. To this end, we categorized the smoothing parameters into three groups, corresponding to the three scales suitable to studying the urban thermal landscape at the micro-scale, meso-scale, and regional scale, respectively. The identified scales can then be matched with various applications in urban planning and environmental management.

Index Terms—ASTER imagery, green vegetation, impervious surface, modeling, pattern recognition, urban heat island

I. INTRODUCTION

Land and surface temperature (LST) and emissivity data derived from satellite thermal infrared (TIR) imagery have been used in urban climate studies mainly for analyzing LST patterns and its relationship with surface characteristics, assessing the urban heat island (UHI), and relating LSTs to surface energy fluxes for characterizing landscape properties, patterns, and processes [1]. Permanent meteorological station data and moving observations using air temperatures cannot provide a synchronized view of temperature over a city. Only remotely sensed TIR data can provide a continuous and simultaneous view of a whole city, which is of prime importance for detailed investigation of urban surface climate. However, it should be noted that LSTs and air temperatures can be very different, especially in summer daytime with clear skies and high solar loading. LSTs show much larger spatial variability associated with the properties of the surface, whereas air temperatures are much less variable due to mixing of heat by the atmosphere. Among the majority of the existing literature in remote sensing, there is confusion between LST patterns and UHIs. Nichol suggested that the concept of a “satellite derived” heat island is largely an artifact of low spatial resolution imagery used, and the term “surface temperature patterns” is more meaningful than surface heat island [2]. The UHI was first defined in terms of air temperatures to represent the difference between warmer urban compared to cooler rural areas, but sufficient care must be taken to defining the urban and rural surfaces chosen for the comparison [3]. The definition of UHI has since been adapted to looking at spatial patterns of surface temperature using remote sensing [4]; however, there were different opinions about what constitute the representative “urban” and “rural” surfaces. An appropriate rural reference should be from a representative land cover type typical of non-urban surroundings of a city and should be from the same type of topographical setting without major elevation change. Stewart and Oke recently developed a classification scheme of urban land cover zones, which can be used to select representative surfaces for studies of surface and air temperature heat islands [5]. When imaged at high spatial resolution, the apparent UHI for surface temperatures may potentially be very large since extremely hot and cold individual surfaces (pixels) may be seen and measured. Therefore, what needs to be considered is an appropriate scale for assessing the UHI based on LSTs. It is of great scientific significance to investigate how satellite-derived LSTs can be utilized to characterize UHI phenomenon and to derive UHI parameters. Few studies have focused on the modeling of UHI by deriving its parameters, such as magnitude / intensity, center, spatial extent, shape, and orientation, from LST measurements. Streutker used AVHRR data to quantify the UHI of Houston, Texas, as a continuously varying two-dimensional Gaussian surface superimposed on a planar rural background, and to derive the UHI parameters of magnitude, spatial extent, orientation, and central location [6]-[7]. Rajasekar and Weng applied a non-parametric model by applying Fast Fourier Transformation (FFT) to MODIS imagery (in 2005) for characterization of the UHI over time in the metropolitan Indianapolis (city of Indianapolis and eight neighboring counties) [8]. It is found that the magnitude of the
UHI varied from 1-5 °C and 1-3 °C over the daytime and nighttime images, respectively. Rajasekar and Weng further applied a process Gaussian model to Landsat-5 (from years 1985 and 1995) and Landsat-7 (from year 2000) images for the city of Indianapolis to examine changes in the center and the spatial extent of the UHI from 1985 to 2000 [9]. Imhoff et al. utilized impervious area surface from the USGS NLCD 2001 dataset and LST data from MODIS averaged over three annual cycles (2003-2005) to assess the UHI skin temperature magnitude and its relationship to development intensity, size, and ecological setting for 38 of the most populous cities in the continental United States [10]. Their results show that the UHI magnitude increases with city size and is seasonally asymmetric with a 4.3 °C temperature difference in summer and 1.3 °C in winter. In spite of these research efforts, characterizing and modeling UHIs across various spatial scales in the urban areas, especially estimation of UHI intensity / magnitude based on multi-temporal and multi-resolution TIR imagery remains a promising research direction given the increased interest among the urban climate and the environment science communities.

Another important issue in urban thermal remote sensing is how to deepen the understanding of the relationship between the reception/loss of radiation and urban surface characteristics. There has been a tendency to use thematic land use and land cover (LULC) data for simple correlation between LST and LULC types [11]. The relationship between LST and vegetation indices (e.g., NDVI) has been extensively documented [12], and shows a negative correlation. Recent studies have used impervious surface (IS) area [13]-[15], which is positively correlated with LST, and has the advantage of less seasonal variability. Most recent advances include the development of sub-pixel quantitative surface descriptors for assessing the interplay between urban material fabric and thermal behavior [16], and employing the landscape ecology approach to identify the operational scales across urban thermal landscapes [17]-[18]. However, few published works have related sub-pixel biophysical descriptors to the UHI parameters, derived from the optical and TIR data of satellite images respectively.

This research develops a modeling approach to characterize UHI phenomenon at various spatial scales, and to derive UHI intensity so as to relate it to remotely sensed biophysical parameters. Four ASTER images over the city of Indianapolis were used for the analysis. These images were acquired in different seasons/years, so we can examine the applicability of the modeling approach for multi-temporal satellite images. Specific objectives of this research are three-fold: (1) to characterize the spatial patterns of UHIs and to estimate UHI intensity by using LSTs; (2) to develop greenness and imperviousness indices based on convoluted spectrally unmixed green vegetation (GV) and IS fractions; and (3) to investigate the relationship between the UHI intensity and the indices of greenness and imperviousness.

II. DATA

The City of Indianapolis, located in Marion County, Indiana has been chosen as the area of study (Fig. 1). With over 0.8 million population, the city is the nation’s twelfth largest one. 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. It is one of the three major cities in the Midwest having an annual population growth rate over 5%. The areal expansion is through encroachment into the adjacent agricultural and nonurban land. As a result, a new metropolitan area of nine counties (Marion, Hamilton, Johnson, Madison, Hancock, Shelby, Boone, Hendricks, Morgan) is forming, comprised of approximately 9,100 sq. km. in area and 1.6 million population in 2000. Certain decision-making forces have encouraged some sectors of the Metropolitan Indianapolis (especially towards north, northeast, northwest, south, and more recently towards southwest) to expand faster than others. Detecting its urban expansion and the relationship to UHI development is significant to mitigate its effect, and also provides important insights into the city’s future urban planning and environmental management.

The primary remote sensing data used in this research include Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) [19] and US Geological Survey’s Digital Raster Graphic imagery. ASTER images were acquired on Oct. 3, 2000 (12:00:51 eastern standard time), June 16, 2001 (11:55:29), April 5, 2004 (11:46:39), and Oct. 13, 2006 (11:40:01). Although we were approved by JPL NASA to acquire four images annually for the study area, clouds and other weather conditions have prevented us to get a quality image every season. These selected images are the best available ones, which we intend to use for examination of the seasonal variability of urban landscape and the effect of urban growth on the UHI. The local times of satellite overpasses were all between 11:40 AM and 12:01 PM. Satellite detection of UHIs using TIR sensors has demonstrated that the UHI intensity reaches the greatest in the daytime and in the warm
season and least at the nighttime – the opposite to the UHI results based on the measurement of air temperatures [20].

ASTER data, including the level 1B registered radiance at the sensor and the level 2 surface reflectance, kinetic temperature and emissivity data, were obtained. The theoretical basis and computation algorithm for surface reflectance products have been reported by Thome et al. [21]. The algorithm for converting ASTER thermal infrared measurements to LSTs has been reported by Gillespie et al. [22] and the ASTER Temperature / Emissivity Working Group (TEWG) [23], with which surface kinetic temperature is determined by applying Planck’s Law using the emissivity values from the Temperature-Emissivity Separation (TES) algorithm. LST values calculated using this procedure are expected to have an absolute accuracy of 1-4 K and relative accuracy of 0.3 K, and surface emissivity values an absolute accuracy of 0.05-0.1, and relative accuracy of 0.005 [23].

Separated single bands of VNIR, SWIR, and TIR data were first stacked into one set. An image-to-image registration was conducted. The ASTER images were georectified to Universal Transverse Mercator (UTM) projection with NAD27 Clarke 1866 Zone 16, by using 1:24000 Digital Raster Graphic (DRG) maps as the reference data. Approximately 40-50 ground control points were chosen for each image. The images were re-sampled to the spatial resolution of 15 m with the nearest-neighbor resampling algorithm. The root mean square error (RMSE) for the geocorrection was all less than 0.3 pixel. An improved image based dark object subtraction model has proved effective and was applied to reduce the atmospheric effects [24]-[25].

III. METHODOLOGY

A. Linear Spectral Mixture Analysis

Linear spectral mixture analysis (LSMA) is regarded as a physically based image processing technique that supports repeatable and accurate extraction of quantitative sub-pixel information [26]-[28]. It assumes that the spectrum measured by a sensor is a linear combination of the spectra of all components within the pixel [27], [29]. Because of its effectiveness in handling the spectral mixture problem, LSMA has been widely used in estimation of vegetation cover [30]-[32], in land cover classification and change detection [33]-[34], and in urban studies [35]-[36]. In this study, LSMA was employed to develop green vegetation, soil, and impervious surface fraction images. A constrained least-squares solution [26] was applied to unmix the nine VNIR and SWIR bands of ASTER imagery into fraction images, including high albedo, low albedo, vegetation, and soil fractions.

With the LSMA approach, the selection of appropriate endmembers is a key for successful development of high-quality fraction images. In previous studies, many methods have been developed for endmember selection [37]. Image-based endmembers are well accepted, because image endmembers can be easily obtained from the image feature space. Moreover, no calibration is needed between selected endmembers and the spectra measured. Image endmembers are frequently derived from the extremes of the image feature space, which are assumed to represent the purest pixels in the image [28]. The LSMA approach requires that the number of endmembers derived should not exceed the number of the image bands plus one. Theoretically speaking, ten endmembers may be developed with the nine VNIR and SWIR bands of an ASTER image. However, high correlation between certain bands (especially between the six SWIR bands) limits the usage of a large number of endmembers. We found that the NIR band had very low correlation with any of the other ASTER bands, indicating its independency in information. The correlation coefficients between visible bands and between SWIR bands, especially between SWIR 5-9 bands, were frequently greater than 0.97. The principal component analysis result indicated that the first four components accounted for 99.98% of the overall variance. This suggests that a maximum of five endmembers may be developed in this study.

Endmembers were initially identified from the ASTER images in reference to high-resolution aerial photographs. Four types of endmembers were selected: green vegetation, soils (including dry soil and dark soil), low albedo (asphalt, water, etc.), and high albedo surfaces (concrete, sand, etc.). Vegetation was selected from the areas of dense grass and pasture. Different types of impervious surfaces were selected from building roofs, airport runway, highway intersections, etc. Soils were selected from bare grounds in agricultural lands. Next, these initial endmembers were compared with those endmembers selected from the image scatter plots. The endmembers with similar spectra located at the extreme vertices of the scatter plots were finally selected. To find best quality of fraction images for estimation of impervious surfaces, different combinations of endmembers were examined and compared. Visualization of fraction images, analysis of fractional spectral properties of representative land cover types, and assessment of error images were conducted to determine which combination provided the best fractions for each image. The criteria for selecting the most suitable fraction images were based on: (1) high-quality fraction images for the urban landscape, (2) relatively low error, and (3) the distinction among typical LULC types in the study area. A constrained least-squares solution was applied to unmix the nine VNIR and SWIR bands of ASTER images into fraction images. Fig. 2 shows fraction image of green vegetation and impervious surface at the four dates.

![Fraction images of green vegetation (first row) and impervious surface (second row) at the four imaging dates, derived from linear spectral mixture analysis. Fraction value ranges from 0 to 1. Brighter tone is associated with more abundance of green vegetation/impervious surface.](image-url)
B. Estimation of Impervious Surfaces

Impervious surface was estimated based on the relationship between the reflectance of two endmembers (high- and low-albedo) and the reflectance of the impervious areas. By examining the relationships between impervious surfaces and the four endmembers, Wu and Murray found that impervious surfaces were located on or near the line connecting the low albedo and high albedo endmembers in the feature space [35]. An estimation procedure was thus developed based on this relationship by combining the fractions of high albedo and low albedo endmembers. The IS image can be computed as:

\[ R_{imp,b} = f_{low,b}R_{low,b} + f_{high,b}R_{high,b} + e_b \]  

(1)

Where \( R_{imp,b} \) is the reflectance spectra of impervious surfaces for band \( b \), \( f_{low} \) and \( f_{high} \) are the fractions of low albedo and high albedo, respectively, \( R_{low,b} \) and \( R_{high,b} \) are the reflectance spectra of low albedo and high albedo for band \( b \), and \( e_b \) is the unmodeled residual. The fitness of this two-endmember linear spectral mixture model has been demonstrated by Wu and Murray for the central business district of Columbus, Ohio, USA. We tested this model in the central part of the study area, the central business district (CBD) of Indianapolis, and found an excellent fit with mean RMSE value of less than 0.02 for all images. Following the Wu and Murray’s method [35], four IS images were computed.

Due to spectral confusion, non-impervious materials of both low reflectance (e.g., water and shades) and high reflectance (e.g., sand and dry soils) may be contained in the low- and high-albedo image fractions. These non-impervious materials should be removed to improve the quality of impervious surface maps. Lu and Weng used LST to develop an image mask to remove those materials, because there was a temperature difference between impervious surfaces and non-impervious surfaces [38]. It is found that the method was fairly effective to remove non-impervious pixels. In this research, we extended this method by using LST and LULC maps and their various combinations as image masks for refining IS images. These image masks were built based on the relationship of individual LULC type with the abundance of impervious surfaces and their significance in the maximum, minimum, and mean LSTs. In particular, the maximum and mean temperatures of non-impervious covers (such as water, agricultural land, and forestland) and the minimum temperature of impervious covers (such as urban/built-up land) were tested for their effectiveness as image masks [39]. The second row of Fig. 2 shows the resultant four impervious surface images.

For the accuracy assessment of impervious surface images, a total of 400 samples were selected using a stratified random sampling scheme. The size of each sample equaled to 6 by 6 pixels, which had the ground dimension of 90m by 90m. For each sample, the boundary of impervious surface polygons was digitized on the corresponding DOQQ (Digital Ortho Quarter Quadrangles) using ArcGIS. The alignment of DOQQ with ASTER images was ensured to be very precise with registration error of smaller than 0.001 pixel. After the digitization, the proportion of impervious surface area was computed by dividing the area of impervious surface by the sampling area. The root-mean-square-error (RMSE) was then computed to indicate the accuracy of impervious surface estimation as follows:

\[ RMSE = \sqrt{\frac{\sum_{i=1}^{N} (\hat{I}_i - I_i)^2}{N}} \]  

(2)

Where \( \hat{I}_i \) is the estimated impervious surface fraction for sample \( i \), \( I_i \) is the impervious surface proportion computed from DOQQ, and \( N \) is the number of samples. The computational result indicates that these impervious surface maps yielded RMSE of 16.3% (October 3, 2000), 17% (June 16, 2001), 20.2% (April 5, 2004), and 24.6% (October 13, 2006), respectively.

C. Kernel Convolution

A kernel convolution model implementing Gaussian bi-variate function was employed to characterize LST, GV, and IS data patterns. Higdon explained this process convolution for a single dimensional process and made suggestions for its extension to two or three dimensions [40]. The kernel convolution results in smoothened data surfaces showing the spatial patterns of LST, GV, and IS across scales. We have written a computer program for this task using the language R. In order to understand how the kernel convolution works, we first need to know the definitions of kernel and convolution, and then the process convolution, which was extended in this study to model LST, GV, and IS as a 2-dimensional Gaussian process.

Kernel smoothing refers to a general class of techniques for non-parametric estimation of functions. The kernel is a smooth positive function \( k(x, h) \) which peaks at zero and decreases monotonically as \( x \) increases in size. The smoothing parameter \( h \) controls the width of the kernel function and hence the degree of smoothing applied to the data [41]. One can define the kernel as a function \( k \) that for all \( x, h \in X \) satisfies [42]:

\[ k(x, h) = (\phi(x), \phi(h)) \]  

(3)

where \( \phi \) is a mapping from \( X \) to an (inner product) feature space \( F \).

\[ \phi: x \rightarrow \phi(x) \in F \]  

(4)

The degree of smoothing (i.e., the extent of standard deviation of the Gaussian distribution) to be performed by the kernel is a function defined by its bandwidth \( h \). The value of \( h \) increases as the degree of smoothing increases and vice versa.

The convolution of \( f \) and \( g \) could be written as \( f * g \). It is defined as the integral of the product of the two functions after one is reversed and shifted.

\[ (f * g)(t) = \int f(\tau) g(t - \tau) \, d\tau \]  

(5)
If $X$ and $Y$ are two independent variables with probability densities $f$ and $g$, then the probability density of the sum $X + Y$ is given by the convolution $f * g$. For discrete functions, one can use a discrete version of the convolution. It is given below by Equation (6):

$$(f * g)(m) = \sum_n f(n)g(m - n)$$ (6)

A Gaussian process over $R^d$ is to take the independent and identically distributed Gaussian random variables on a lattice in $R^d$ and convolve them with a kernel. The process involves successive increase in the density of the lattice by a factor of two in each dimension and reduces the variance of the variates by a factor of 2$d$, leading to a continuous Gaussian white noise process over $R^d$. A Gaussian white noise is a white noise with normal distribution. The convolution of this process can be equivalently defined by using some covariogram in $R^d$. The process of convolution gives very similar results to defining a process by the covariogram.

Let $y_{(1,1)}$, ..., $y_{(i,j)}$ (where $y$ is a two dimensional matrix of $(1,1), ..., (i,j)$) be recorded over the two dimensional spatial locations $s_{(1,1)}, ..., s_{(i,j)}$ in $S$, a spatial process $z = (z_{(1,1)}, ..., z_{(i,j)})^T$, and Gaussian white noise $\varepsilon = (\varepsilon_{(1,1)}, ..., \varepsilon_{(i,j)})^T$ with variance $\Sigma'_\omega$. The spatial method represents the data as the sum of an overall mean $\mu$.

$$y = s + z + \varepsilon$$ (7)

where the elements of $z$ are the restriction of the spatial process $z(s)$ to the two dimensional data locations $s_{(1,1)}, ..., s_{(i,j)}$. $z(s)$ is defined to be a mean zero Gaussian process. Rather than specifying $z(s)$ through its covariance function, it is determined by the latent process $x(s)$ and the smoothing kernel $k(s)$. The latent process $x(s)$ is restricted to be non-zero at the two dimensional spatial sites $s_{(1,1)}, ..., s_{(a,b)}$, also in $S$ and define $x = (x_{(1,1)}, ..., x_{(a,b)})^T$ where $x_{(a,b)} = x_{(a,b)}$ and $p = (1,1), ..., (a,b)$. Each $x_{(a,b)}$ is then modeled as independent variable and draws from a $N(0, \Sigma'_\omega)$ distribution. The resulting continuous Gaussian process is then:

$$z(s) = \sum_{p=(1,1)}^{(a,b)} x_p k(s - \omega_p)$$ (8)

where $k(-\omega_p)$ is a kernel centered at $\omega_p$. This gives a linear model:

$$y = \mu_{(i,j)} + Kx + \varepsilon$$ (9)

where $l_{(i,j)}$ is the $(i,j)$th vector of $l$'s. The elements of $K$ are given by:

$$K_{pq} = k(s_p - \omega_q) x_q$$ (10)

$$x \sim N(0, \sigma^2_{(a,b)})$$ (11)

and

$$\varepsilon \sim N(0, \sigma^2_{(i,j)})$$ (12)

The smoothing kernel or the parameter, as described in the Equation (10), defines the degree of smoothing and is a crucial parameter in the kernel convolution modeling. The degree of smoothing is inversely proportional to the smoothing kernel. In other words, as the value of the smoothing kernel decreases, the degree of smoothing over the spatial domain increases. When the degree of smoothing reached the maximum value of one, a kernel-convoluted image was formed; whose values were equivalent to the mean of the original image. When the degree of smoothing was minimum (i.e., zero smoothing), the final kernel convoluted image would be the same as that of the original image.

IV. RESULTS

A. UHI Intensity across Spatial Scales

By changing the smoothing parameter from 0.05 to 1.0, with an incremental rate of 0.05, the kernel convolution modeling resulted in 20 convoluted maps for each LST, GV, and IS image. Fig. 3 shows the convoluted LST maps with the smoothing parameter ranging from 0.05 to 0.9 in the four dates. We further computed the magnitude (intensity) of UHI by subtracting the minimum temperature value from the maximum temperature value of each convoluted image. Table 1 shows the UHI intensity value at each smoothing level. An examination of data distribution pinpointed two breaks at the smoothing level of 0.2 and 0.5. When the smoothing parameter ranged from 0.05 to 0.2, the UHI intensity mostly reached 6 K, peaking around 14 K. Fig. 3 shows that the thermal landscapes of all dates exhibited scattered hot spots to as few as four. These types of landscapes would be suitable for studies at the micro-scale level. The term “surface temperature patterns” is more meaningful here than surface UHI. The information on micro-scale LST patterns may be useful for zoning considerations in the process of city planning and environmental management at the relevant geographical scale. For the purpose of comparison, Table 1 also lists the minimum-maximum temperature differences for the original LST images, which have values from 15.7 K to 18.3K. It has been suggested that the UHI magnitude computed by using single pixel comparison method was strongly influenced by localized extreme temperatures and tended to be several times higher than the Gaussian magnitude [6]. When the smoothing parameter ranged from 0.25 to 0.5, the UHI intensity mostly reached 6 K, subject to the seasonality. Two to four hot spots can be identified from each image, with the largest hot spot in the city center corresponding to its central business district. These hot spots can be directly linked to the biophysical structure of the city and the structure of the urban atmosphere, and are thus suitable for studies at the meso-scale (i.e., the city scale). These types of studies would provide valuable information for city planning, especially for transportation, large infrastructures, and clustered development (e.g., leap-frog development). Fig. 3 shows that the hot spots identified at this scale appeared to associate with major infrastructures and urban clusters in the city (e.g., major transportation network, CBD, commercial/industrial cluster, etc.). By setting the smoothing parameter in the range of 0.55 to 1.0, the kernel convolution modeling yielded consistently...
single-hot spot thermal landscape pattern. This kind of spatial pattern is essentially in agreement with the conventional definition of UHI, which reveals the difference between the urban and the rural temperatures of a specific city. It should be noted that the conventional definition of UHI being referred to is the air temperature heat island, which has shown the greatest intensity at night [43]. Most UHI intensity values computed in this study ranged from 1.5 to 3.5 K, despite of over-time changes in the UHI center position, spatial extent and shape. The studies on such UHI pattern and its dynamics would contribute to understanding of urban climate. More importantly, the modeling at this macro-scale would allow for concurrent comparison of UHIs across nearby cities in the region. The information provided by such studies would be beneficial for regional planning and watershed management of a city-region (i.e., an urban cluster).

By comparing the convoluted LST maps of different dates at the same smoothing levels, it is possible to observe the changes in the urban thermal landscape pattern over the time. The changes in the thermal pattern reflected largely the changes in “surface” factors, including the thermal properties of surface materials, the composition and layout of LULC types, and anthropogenic effects related to the existence of automobiles, air conditioning units, industries, and air pollution. As these images were acquired in different seasons (spring, summer, and fall) spanning several years (2000 through 2006), the variation in the surface factors embraced the effects of seasonal change and long-term change due to urban sprawl. The UHI intensity was greatest in the summer (June 16, 2001) as far as the macro- and meso-scales were concerned. This observation is consistent with the findings in previous literature [20].

However, at the micro-scale, the UHI intensity was strongly influenced by pixels with extreme LST values. At all smoothing levels, the UHI intensity was lowest on October 13, 2006. The only exception was observed at the smoothing parameter 0.05, when the UHI intensity was detected to be the greatest on October 13, 2006. This anomaly can be explained by the co-existence of the extreme low LST (291K) and the extreme high LST (305K) on that date. A comparison between Fig. 3(C) and 3(D) offers some useful information about the effect of urban development on the UHI pattern, since the two images were acquired at nearly anniversary dates. At the micro-scale, we may not be able to visualize much difference in the thermal pattern. However, at the meso- and macro-scale, the difference was noticeable. The UHI was more spread-out along the west-east corridor in 2000, reflecting well the layout of historical urban development in Indianapolis. LULC changes and especially recent urban build-ups (commercial, industrial, and residential developments along the highways) in the south of the city in Perry Township (see Fig. 1) had elongated the UHI from the CBD to this newly developed area.

### Table I

<table>
<thead>
<tr>
<th>Smoothing parameter</th>
<th>UHI intensity (K)</th>
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<tr>
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#### B. Relationship between UHI Intensity, Greenness and Imperviousness

The urban-rural temperature disparity is largely modulated by the differences in environmental conditions between the urban and rural areas. In this study, we developed a greenness and an imperviousness index to set apart the urban and the rural biophysical environments. Because the kernel convolution process removed the extreme values and generated more uniform images, we adapted the mean value of each convoluted image of GV and IS as the base value, indicating the mean rural environmental conditions [44]-[45]. By subtracting the mean value from the maximum value, an index of greenness or imperviousness for each convoluted image was computed. In each imaging date, there were 20 convoluted GV and IS images. Therefore, 20 greenness and imperviousness indices were calculated.

Correlation analysis was performed between the 20 UHI intensity values and the 20 greenness values, so was between the 20 UHI intensity values and the 20 imperviousness values. Table 2 shows the result of correlation analysis between the...
UHI intensity and greenness, as well as between the UHI intensity and imperviousness index. The significance of each correlation coefficient was determined by using a one-tail Student's t-test. The UHI intensity was found highly positively correlated with both greenness and imperviousness, regardless of seasonality. That is, the more contrast in the biophysical conditions between the urban and the rural in respect to GV and IS, the more intensive the UHI would tend to be. As IS is usually inversely related to GV cover in urban areas, a higher contrast in greenness tends to associate with the larger difference of imperviousness. Correlation analysis was further conducted between the UHI intensity values and the mean GV / IS values. Table 2 further shows that the UHI intensity was negatively correlated to the mean GV value, implying that the greater abundance of GV contributed to reduce the UHI effect. This finding is in good agreement with previous studies [12]. Furthermore, mean LST values were found to have highly positive correlation with mean IS values, which is consistent with some recent researches [13]-[15]. However, by comparing the mean IS value and the imperviousness index that we developed in this study, it is found that imperviousness was more closely correlated to the UHI intensity. Similarly, we observed that the greenness index had a stronger correlation with the UHI intensity than the mean GV value.

### Table II.

<table>
<thead>
<tr>
<th>Date of Image</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>UHI intensity vs. Greenness</td>
<td>UHI intensity vs. Imperviousness</td>
<td>UHI intensity vs. Mean GV values</td>
<td>Mean LST vs. Mean IS values</td>
</tr>
<tr>
<td>Oct 3, 2000</td>
<td>0.9924</td>
<td>0.9932</td>
<td>-0.9849</td>
<td>0.9744</td>
</tr>
<tr>
<td>June 13, 2001</td>
<td>0.9944</td>
<td>0.9981</td>
<td>-0.9135</td>
<td>0.9849</td>
</tr>
<tr>
<td>April 5, 2004</td>
<td>0.9573</td>
<td>0.9822</td>
<td>-0.9846</td>
<td>0.9888</td>
</tr>
<tr>
<td>Oct 13, 2006</td>
<td>0.9868</td>
<td>0.8833</td>
<td>-0.9069</td>
<td>0.9685</td>
</tr>
</tbody>
</table>

**V. DISCUSSION AND CONCLUSIONS**

A key issue in thermal remote sensing of urban areas is how to use pixel-based LST measurements to characterize and quantify UHIs observed at various spatial scales. This study has employed a kernel convolution modeling method to characterize the UHI in Indianapolis as a two-dimensional Gaussian process. The modeling results allowed us to analyze several key UHI parameters, including the intensity, center, spatial extent, and orientation, but this study focused on the UHI intensity only. Moreover, we extended our previous efforts for employing LSMA to extract sub-pixel urban biophysical variables (i.e., GV and IS) [16], [39], but focused on the improvement of extraction quality and the comparability of these variables from multi-temporal ASTER images. Finally, we developed two new indices (greenness and imperviousness) based on the convoluted images of GV and IS fractions. It is found that the UHI intensity had an extremely strong positive correlation with both greenness and imperviousness indices, which indicated the urban-rural contrast in the abundance of GV / IS. The correlations were stronger than previous LST indicators such as GV abundance and IS coverage explored in the remote sensing literature.

Various methods and algorithms have been developed for characterizing surfaces in the spatial domain. For example, kriging and thin plate spline models have been used successfully for spatial estimation, while Cellular Automaton-based models are widely used for prediction/simulation of urban LULC change. These algorithms characterize spatial surfaces from a global or whole map view without considering the variations across the space. This failure to adapt to local variability, or heterogeneity, in the unknown process is of particular importance in environmental, geophysical, and other spatial datasets, in which domain knowledge suggests that in most cases the phenomenon may be non-stationary [46]. In remote sensing studies of UHIs, even though a single parametric model could be defined for the analysis of a single image, it would be difficult to apply the same model to multi-temporal and multi-sensor images in order to perform a comparative analysis and thus to conduct spatio-temporal dynamic modeling and analysis. Because the UHI effect is closely related to the composition and layout of LULC, urban growth frequently generates an important impact on the dynamics of UHI over the space and time [45], [47], [48]. The fact that urban growth is a non-stationary process over the space and that factors underlying LULC change may vary from place to place [49] implies that the same set of underlying factors may yield various effects in different cities / regions and at different geographical scales, leading to different patterns and processes of urbanization and UHI. A method / algorithm that can account for the spatial non-stationarity, such as the process kernel convolution model used in this study, is proper for UHI characterization and modeling.

In this study, we utilized the smoothing kernel to characterize the spatial non-stationarity in the urban thermal landscape and to link the UHIs with the biophysical parameters. This characterization and the linkage allow us to examine UHI as a scale-dependent process. Oke suggested that there were often several linked UHIs in one city, and that each distinguished from one another mainly by scales imposed by the biophysical structure of a given city and the structure of the urban atmosphere [50]. Each UHI is therefore required measurement arrays appropriate to the scale [50]. Most previous literature failed to account for the existence of multiple UHIs in a city [6], [10]. By changing the smoothing parameter, this study was able to characterize multiple UHIs of various sizes (spatial extent) in Indianapolis. Further, we categorized the smoothing parameters into three groups. Each group was found suitable to study the urban thermal landscape at a particular spatial scale, i.e., the micro-scale, meso-scale, and regional scale, such that the identified scales can be matched to various applications in urban planning and environmental management. Further studies are necessary to reconcile studies of the UHI scale (e.g., this study) and the operational scale of LST (e.g., [12], [18], [51], [52]) in order to better understand urban thermal landscapes and dynamics from the remote sensing perspective.


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