Urban heat island monitoring and analysis using a non-parametric model: A case study of Indianapolis

Umamaheshwaran Rajasekar, Qihao Weng *

Center for Urban and Environmental Change, Department of Geography, Indiana State University, USA

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A B S T R A C T

A procedure for the monitoring an urban heat island (UHI) was developed and tested over a selected location in the Midwestern United States. Nine counties in central Indiana were selected and their UHI patterns were modeled. Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature (LST) images taken in 2005 were used for the research. The images were sorted based on cloud cover over the study area. The resulting 94 day and night images were used for the modeling. The technique of process convolution was then applied to the images in order to characterize the UHIs. This process helped to characterize the LST data into a continuous surface and the UHI data into a series of Gaussian functions. The diurnal temperature profiles and UHI intensity attributes (minimum, maximum and magnitude) of the characterized images were analyzed for variations. Skin temperatures within any given image varied between 2–15 °C and 2–8 °C for the day and night images, respectively. The magnitude of the UHI varied from 1–5 °C and 1–3 °C over the daytime and nighttime images, respectively. Three dimensional (3-D) models of the day and night images were generated and visually explored for patterns through animation. A strong and clearly evident UHI was identified extending north of Marion County well into Hamilton County. This information coincides with the development and expansion of northern Marion County during the past few years in contrast to the southern part. To further explore these results, an Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) 2004 land use land cover (LULC) dataset was analyzed with respect to the characterized UHI. The areas with maximum heat signatures were found to have a strong correlation with impervious surfaces. The entire process of information extraction was automated in order to facilitate the mining of UHI patterns at a global scale. This research has proved to be promising approach for the modeling and mining of UHIs from large amount of remote sensing images. Furthermore, this research also aids in 3-D diachronic analysis.

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1. Introduction

It is often observed that air temperatures in densely urbanized areas are higher than those of the surrounding countryside. Among these urban–rural differences, the most notable and well documented is the phenomenon known as the “urban heat island” (UHI) (Kim and Baik, 2005). In spite of the fact that the temperature differences strongly vary at a micro scale, both in rural and urban areas, the thermal characteristics of the urban terrain at a macro scale constitute a basic factor in the creation of an UHI (Chudnovsky et al., 2004).

Over the past few years, studies have been carried out to understand the UHI using both air (Fast et al., 2005; Friedl, 2002; Kim and Baik, 2005; Mihalakakou et al., 2002) and skin surface temperature data (Dash et al., 2002; Golden and Kalouch, 2006; Jin et al., 2005; Jung et al., 2005; Snyder et al., 1998). UHI analysis performed using in-situ data has the advantage of high temporal resolution and a long data record, but lacks spatial resolution (Hung et al., 2006). This spatial discontinuity caused by using air temperature data can be overcome by using skin temperatures. For a large area, skin temperature can be mapped and studied by using satellite remote sensing data in the infrared spectrum (Stathopoulou et al., 2004; Vogt and Oke, 1998). There have been studies that have contributed to the use of remote sensing imagery for understanding the UHI effects. Lo et al. (1997) analyzed the UHI effect by using the Advanced Thermal and Land Application Sensor (ATLAS). Weng (2001, 2003) and Weng et al. (2004) have done several studies to analyze the relationship of the UHI effect with respect to the urban factors such as land cover, vegetation and population. Jung et al. (2005) have tried to model the effect of an UHI on vegetation using hyperspectral remote sensing images. Kato and Yamaguchi (2005) analyzed the effect...
of the UHI using Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and Enhanced Thematic Mapper (ETM+) images. Hung et al. (2006) have assessed the UHI among selected Asian mega cities using images from Aqua and Terra missions.

There has been a considerable amount of research carried out to model the UHI effect. At a practical level, it becomes difficult to generalize the location and distribution of an UHI due to several reasons. These are attributed mainly to the shape and extent of the city, its layout, the nature and type of the surrounding areas, and the resolution of the imagery used to characterize the phenomenon. These factors not only affect the size and shape of the UHI, but they also affect its magnitude. Another characteristic that proves problematic is the boundary between the urban and rural areas is never crisp. It is an area of transition, which is mostly fuzzy. It is important to incorporate this aspect into the UHI modeling, rather than separately modeling the urban area with one method and the rural area with another.

The main objectives of this research are twofold. First, this paper intends to develop a method for characterizing an UHI as a continuous function that includes both urban and rural surfaces. This helps to visualize the pattern of the UHI over the entire study area. There have been several studies that have used statistical methods such as variograms (Bottýan and Unger, 2003) and non-linear parametric models (Streutker, 2003) to characterize the UHI from remote sensing data sets. Even though these processes are effective for analyzing a single or a small set of images, they prove to be inefficient in modeling an UHI from a large set of images. The reason for this inefficiency is that these processes are image-dependent and require manual interference during the various stages of process execution. In order to overcome these difficulties, in this research, a non-parametric model using fast Fourier transformation (FFT) will be utilized to effectively and efficiently characterize the UHI over space.

The second objective of this research is to analyze the UHI pattern over space and over time. It becomes important to monitor the behavior of the UHI with respect to one location over time. This would aid in developing a better understanding of urban temperature and the contribution of the urban surfaces toward the total energy balance. Theoretically, if land use does not change, the UHI should remain relatively constant with respect to its surrounding rural background. However, this is often not the case. There have been studies which have demonstrated that yearly mean of an UHI is negatively correlated to the rural regions (Streutker, 2002). Therefore, the main goal of this research is the development of a model for an UHI that will expand our current understanding of the phenomenon. Further, as a test for validity of the developed UHI model, the characterized images were analyzed with respect to LULC.

2. Study area and data

2.1. Study area

The main motivation behind this research is to develop a general model for monitoring UHIs using high temporal and low spatial resolution images. As a sample case, metropolitan Indianapolis was selected, both the state capital and the county seat of Marion County, its population is 791,926 according to the 2000 Census, making it Indiana's most populous city and the state capital and the county seat of Marion County, its population is 791,926 according to the 2000 Census, making it Indiana's most populous city and the county seat of Marion County. The assumption is that including counties that have a greater percentage of rural areas would help the model in characterizing the UHI effectively with respect to its rural background. Only the parts of Clinton, Tipton and Madison Counties present within a single scene were used. The main rationale for not merging two scenes within this research is that we are interested in the UHI effect in the city of Indianopolis (which is located within Marion County). The inclusion of other areas from Clinton, Tipton and Madison Counties would not have impacted the results. Nevertheless, the purpose including these counties (in this case part of three counties and all of five counties) was to create a more comprehensive understanding of the UHI. The UHI phenomenon is most prevalent within urban areas and the effect of the phenomenon could be better understood by contrasting it to its rural surroundings. Theoretically, a portion of area surrounding Marion County composed of parts of eight counties would have been sufficient for such an analysis. However, the complete data for five counties were included as this additional information would not impact the results of the model.

2.2. Data

Land surface temperature and emissivity for large areas (regional and global scales) can only be derived from surface-leaving radiation measured by satellite sensors (Dash et al., 2002). Newer satellite systems such as Moderate Resolution Imaging Spectroradiometer (MODIS) include features to allow for easier calibration and provide surface temperature as a standard product. In this study, land surface temperature (LST) information was utilized, as exemplified by the MODIS (Terra and Aqua satellite missions) sensor. The main rationale for selecting the MODIS imagery was due to its high temporal resolution. The MODIS global daily daytime and nighttime LST are distributed on a daily basis by the land process data archive center (LPDAC). Therefore, this data would not only aid in understanding the UHI on a spatial scale, but also on the temporal scale. Secondly, the extraction of information from such abundant data source is important (Velickov et al., 2000). MODIS is carried on the National Aeronautics and Space
Administration’s (NASA’s) Terra satellite launched in December 1999 and later on the Aqua satellite. The UHI effects are found in terms of skin temperature anomalies during both daytime and nighttime (Jin et al., 2005). Therefore, the satellite-measured skin temperature \( T_{\text{skin}} \) derived from long wave bands that detect surface emissions were used for this study. Thirdly, MODIS was used because of its global coverage. Radiometric calibration in multiple thermal infrared bands designed for retrievals of LST and atmospheric properties. Specifically, bands 3–7, 13 and 16–19 are used for classification of land cover to infer emissivity; band 26 is used to detect cirrus clouds, and thermal bands 20, 22, 23, 29, 31 and 32 correct for atmospheric temperature and water vapor profiles (Wan and Dozier, 1996). The day/night LST algorithm is generated from a pair of daytime and nighttime L1B data using the seven thermal infrared (TIR) bands, atmospheric temperature and water vapor (Wan, 2006). The algorithm has previously shown promising results (Dash et al., 2002).

After the initial data acquisition process, the acquired images were projected to Universal Transverse Mercator (UTM) zone 16N, Datum (WGS 84) and the grid sizes of the images were reduced by creating subset images to cover the regions under study (i.e. the nine counties). The subset images formed an 87 × 89 grid with each grid cell having a 1 km resolution. The single LST image from MODIS used in this study did not cover the entire area of Boone, Hamilton and Madison counties. The omission of this small area was based on the assumption that our main focus was on Indianapolis and these missing rural regions would not significantly impact the analysis.

3. Methodology
The temperature values within the subsets exhibited considerable variation (Fig. 3). This effect might be attributed to the mixed pixel problem, the presence of ecological factors (such as wind, building shadow and haze) and the type and nature of the surface (i.e. land cover and land use). The problem of missing pixels was also widely evident within all subsets due to noise such as cloud cover, water logging due to rain, snow, etc. It was necessary to remove the images with high number of missing pixels from the calculation to facilitate an efficient analysis of the results. Since there are no established standards stating that a certain number of missing pixels would effectively reduce the amount of uncertainty (Openshaw, 1999) for the given process, an approximate amount
Table 1 The LULC classification and their corresponding percentage of pixels within each image for ASTER 2004

<table>
<thead>
<tr>
<th>LULC Description</th>
<th>% Pixels</th>
<th>Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impervious surfaces</td>
<td>31.96</td>
<td>Urban</td>
</tr>
<tr>
<td>Barren land</td>
<td>0.63</td>
<td>Urban</td>
</tr>
<tr>
<td>Grassland</td>
<td>29.51</td>
<td>Urban</td>
</tr>
<tr>
<td>Agricultural land</td>
<td>6.68</td>
<td>Rural</td>
</tr>
<tr>
<td>Forest</td>
<td>28.24</td>
<td>Rural</td>
</tr>
<tr>
<td>Water</td>
<td>2.98</td>
<td>Rural</td>
</tr>
</tbody>
</table>

This research is targeted toward the analysis and monitoring of the UHI effect at a broader scale (i.e., city of Indianapolis and its surrounding counties). In order to address the issue of missing pixels, it was assumed that temperature was a continuous variable. Over the years, statisticians have developed several methods of interpolation to overcome the issue of calculating the value of missing data in a spatial context. While various approaches of kriging and thin plate spline models have been applied successfully for spatial process estimation, they have the weakness of being global models in which the variability of the estimated process is the same throughout the domain. The 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 the function may be non-stationary (Paciorek and Schervish, 2006).

In order to overcome this limitation and facilitate the process of automated information extraction from a series of images, a nonparametric model (kernel convolution) was implemented to study the UHI effect.

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 (Bowman and Azzalini, 1997). One can define the kernel as a function $k$ that for all $x, h \in X$ satisfies (Taylor and Cristianini, 2004)

$$k(x, h) = (\phi(x), \phi(h))$$  \hspace{1cm} (1)

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

$$\phi : x \rightarrow \phi(x) \in F.$$  \hspace{1cm} (2)
The degree of smoothing (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 decreases and vice versa. The resulting set of images was then subjected to visual mining by using animation techniques.

3.1. Kernel convolution

This whole subsection is a modification from the paper by Higdon (2002) (also refer to Rajasekar et al. (2007)) in which Higdon explained the process convolution for a single dimensional process and made suggestions for its extension to two or three dimensions. In this study, the same was extended by the authors to model the urban heat island as a two dimensional Gaussian process. The subsequent derivations are an extension from Higdon (2002). A Gaussian process over \( \mathbb{R}^d \) is to take the independent and identically distributed (IID) Gaussian random variables on a lattice in \( \mathbb{R}^d \) 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 reducing the variance of the variates by a factor of 2\( d \), to lead to a continuous Gaussian white noise process over \( \mathbb{R}^d \). A white noise is a (univariate or multivariate) discrete-time stochastic process whose terms are independent and identically distributed (IID), all with zero mean. A Gaussian white noise process over \( \mathbb{R}^d \) is a white noise with normal distribution. The convolution of this process can be equivalently defined using some covariogram in \( \mathbb{R}^d \). The process of convolution gives very similar results to defining a process by the covariogram. Nevertheless, the convolution construction can be readily extended to allow for non-standard features such as non-stationarity, edge effects, dimension reduction, non-Gaussian fields, and alternative space–time models.

Let \( y_{(1,1)}, \ldots, y_{(i,j)} \) (where \( q \) is a two dimensional matrix of \( (1,1), \ldots, (i,j) \) be data recorded over the two dimensional spatial locations \( s_{(1,1)}, \ldots, s_{(i,j)} \) in \( S \). In this research, the spatial method represents the data as the sum of an overall mean \( \mu \), a spatial process \( z = (z_{(1,1)}, \ldots, z_{(i,j)})^T \), and Gaussian white noise \( \varepsilon = (\varepsilon_{(1,1)}, \ldots, \varepsilon_{(i,j)})^T \) with variance \( \sigma^2 \).

\[
y = s + z + \varepsilon
\]  

where the elements of \( z \) are the restriction of the spatial process \( z(s) \) to the two dimensional data locations \( s_{(1,1)}, \ldots, s_{(i,j)} \). \( z(s) \) 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 nonzero at the two dimensional spatial sites \( \omega_{(1,1)}, \ldots, \omega_{(i,j)} \), also in \( S \) and define \( x = (x_{(1,1)}, \ldots, x_{(i,j)})^T \) where \( x_{(1,1)} = \omega_{(1,1)} ; p = (1, 1), \ldots, (i, j) \). Each \( x_p \) is then modeled as an independent variable and draws from a \( N(0, \sigma^2) \) distribution. The resulting continuous Gaussian process is then:

\[
Z(S) = \sum_{p=(1,1)}^{(i,j)} x_pk(s - \omega_p)
\]  

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

\[
y = \mu l_{(i,j)} + Kx + \varepsilon
\]

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

\[
K_{pq} = k(s_q - \omega_k)x_q
\]

\[
x \sim N(0, \sigma^2 l_{(i,j)}) \quad \text{and} \quad \varepsilon \sim N(0, \sigma^2 z_{(i,j)}).
\]

This results in a basic mixed effect model. The same method could also be extended to incorporate further dimensions. This research concentrates on the two dimensional processes over space. In our research, the size of \( y \) is same as the subset grid of the MODIS LST that was used for the processing and the size of \( p \) is same as the non-cloud or non no-data pixels within each subset grid.

3.2. Optimizing processing efficiency

This subsection is a modification of the derivation provided by Wand and Jones (1995). Discrete kernel estimation of \( \psi(a,b) \) requires \( O(n^2) \) kernel evaluations, which makes its computation very expensive for large sample sizes. One could also use Fourier transform methods to compute the required convolution. The discrete Fourier transform of a complex vector \( Z = (Z_0, \ldots, Z_{N-1}) \) is the vector of \( \hat{Z} = (\hat{Z}_0, \ldots, \hat{Z}_{N-1}) \) where

\[
\hat{Z}_j = \sum_{l=0}^{N-1} z_l e^{2\pi ij/N}, \quad j = 0, \ldots, N - 1
\]

and \( N \) is the number of points.

The vector \( z \) can be recovered from its Fourier transform \( Z \) by applying the inverse discrete Fourier transform Equation:

\[
z_j = N - 1 \sum_{l=0}^{N-1} \hat{Z}_l e^{-2\pi ij/N}, \quad j = 0, \ldots, N - 1.
\]

Discrete Fourier transforms and their inverse can be computed in \( O(N \log N) \) operations using the fast Fourier transform (FFT)
algorithm. The algorithm is fastest when \( N \) is highly composite such as a power of two. The discrete convolution of two vectors can be computed quickly using the FFT by appealing to the discrete convolution theorem, i.e. multiply the Fourier transforms of two vectors element-by-element and then invert the result to obtain the convolution vector. The entire model was executed within 'R', an open source statistical software implementing geospatial data acquisition library (GDAL). Specific scripts were developed to make the process highly user independent. In this study, we used a Pentium IV 2.99 GHz processor with 1 GB of random access memory (RAM) to execute the model.

3.3. Visual mining

The resulting information from the kernel convolution was subjected to exploratory data analysis (EDA). EDA can be described as data-driven hypothesis generation where an examination of the data is performed in search of structures that may indicate deeper relationships between cases or variables. This is in contrast to hypothesis testing, which begins with a proposed model or a hypothesis and undertakes statistical manipulations to determine the likelihood that the data arose from such a model (Hand et al., 2001). Cartographic visualization plays an important role in spatial data handling (Kraak et al., 1997). In this study, animation was used as a technique to analyze the nature of the UHI (daytime and nighttime) and how they behaved during 2005. The results of the process convolution were rendered into a 3-D (in reality 2.5 D) wire frame model plotting the location attributes (latitude and longitude) as the X and Y axes and the derived temperature values as the Z axis. The generated wire frame model for the day and night images were used as frame elements in creating the animation. Apart from visualizing patterns from the animation over time, the characterized temperature images were analyzed in relation to the 2004 ASTER derived LULC data.

4. Results

4.1. Result of kernel convolution

A series of simulations were carried out with varying smoothing parameters. Care was taken that over-smoothing or under-smoothing of the data did not take place. A suitable bandwidth of \( h = 0.15 \) was found to be appropriate. The main objective behind the use of lower bandwidth was to characterize effectively the UHI effect at the city level. Interest was focused on the generalized representation of the phenomenon as a whole rather than the characterization of minor variations in the temperature values at concentrated locations (i.e., micro-scale). Since we were interested in the relative temperature difference between the urban and rural area, the selection of a lower bandwidth would guarantee that the characterization of islands as Gaussian functions over relatively larger areas. Care was also taken that over-smoothing does not take place leading to linear interpolation between the grid cells. Fig. 5 shows a sample result of kernel convolution applied to a LST image. The process convolution technique using FFT was applied for all images. The process of kernel convolution tends to relatively increase (in case of low temperatures) or decrease the temperatures (in case of high temperature) over any image. In this study, this difference in temperature did not exceed \( \pm 3 \)°C. At the same time, the mean temperature within any image (before and after the process convolution) was found to be almost constant. It can also be inferred from the Fig. 5 that the temperature variation within the images was gradual. Even though there was no ideal way of filling data gaps left by clouds, the process convolution technique helped in characterizing these missing values which were present within the initial LST images. The images were successfully characterized into continuous surfaces. This process enhanced the visualization of the UHI over the city of Indianapolis. The characterization of heat islands as a product of two to three functions instead of one main representative function, depending upon the structure of the urban and rural landscape for any given area, aimed in reducing the characterization of minor heat islands that formed around the major UHI. This further concentrated the regional effect of the phenomenon over the entire city and its surroundings rather than characterizing its local effect.

The mean and the magnitude of temperatures (of actual and smoothed images) of each image were then plotted to visualize the temperature profile over time. The magnitude was calculated using the formula \( I_{\text{mag}} = I_{\text{max}} - I_{\text{mean}} \). Where \( I_{\text{mag}} \) stands for the temperature magnitude for the image, \( I_{\text{max}} \) is the maximum temperature and \( I_{\text{mean}} \) is the mean temperature for that particular image. Figs. 6 and 7 visualize the mean temperature profile of the study area from February to November 2005. It can be observed that the mean temperatures were almost the same for the original LST image and the convoluted image. However, there was magnitude of difference in case of the original and convoluted image. This was due to the presence of a few pixels with very high temperatures in the original image and this effect was overcome by the kernel smoothing thereby providing an image with gradual variation in the temperature within these images. From Figs. 6 and 7, one can infer that the skin temperatures within any given image varied between \( 2–15 \)°C and \( 2–8 \)°C for the day and night images, respectively. The UHI magnitude varied from \( 1–5 \)°C and \( 1–3 \)°C over the daytime and nighttime images, respectively. This variation in magnitude, as compared with the range of minimum-maximum of temperature values, established the presence of the UHI. The results obtained for nighttime temperature difference was \( 2–6 \)°C by this research for Marion County and its surrounding areas. This result was found to be very similar to the results published by Chudnovsky et al. (2004) using a high-resolution video thermal radiometer, where the highest mean temperature differences observed was about \( 7–10 \)°C during early morning hours before sunrise. The minor variation in the observed temperatures could be explained by the resolution of the sensor used or by the local variation in LULC. Further, the line fitting provided with Figs. 6 and 7 aids in the visualization of the trend within image series.

The concept of scale is one of the main characteristics that portray geographic data and provides a unique perception of spatial attributes as they relate to form, process and dimension (Lam and Quattrochi, 1992). In this model, the overall accuracy of the kernel smoothing leading to the results would be increased as the resolution increases because the effect of smoothing is dependent upon the pixel resolution in both the \( x \) and \( y \) axes. Nevertheless, the study by Li et al. (2003) has demonstrated that the difference between ASTER (medium resolution) and MODIS was a \( 0.5 \)°C difference in average surface temperature. On grid-cell by grid-cell surface temperature comparison between MODIS and ASTER (both at 925 m resolution) the root mean square error (RMSE) was around 0.9°C and some pixels reached a difference of 2°C due to the different sensors, geo-referencing and the differences in atmospheric and emissivity correction algorithms used to derive the surface temperature (Li et al., 2003). For the UHI studies, this research was more interested in the local effect over the city for which the MODIS imagery proved to be effective. The other aspect that played a major role in the modeling was the temporal effect. The aspect of spatial resolution is generally inversely proportional to the temporal resolution in the case of remote sensing image acquisition, i.e. images of high spatial resolution are generally acquired at low temporal frequencies and vice versa. In our study, we were able to acquire MODIS imagery with a temporal resolution of one image a day. This gave us an option to select the less cloudy imagery from the overall 2005
data set for this study area. This freedom of temporal resolution is restricted in the case of other high spatial resolution images such as Landsat ETM+ and ASTER, etc. However, with new satellites such as FUEGO (a space-based system for service of forest fire fighting management team) being built the limiting aspects of spatial and temporal resolution could be dealt with more effectively. Fig. 8 shows the trend in temperature over the year. This graph was created by calculating the mean temperature for every month. It is evident that the temperature profile for the study area started rising in February and reached a maximum around July and then gradually decreased toward November. Furthermore, it can also be inferred that the mean diurnal temperatures varied between 10–24 °C for any given day. This might be due to the types of LULC present within the study region as different materials behaved differently during varying time periods of the day (Quattrochi and Ridd, 1994).

Apart from characterizing the phenomenon as a continuous surface the method of kernel convolution also facilitated in modeling the data as a series of functions. This model could be further used for extracting the UHI as a series of Gaussian functions instead of representing them as a series of images. This would not only lead to a reduction in the storage space required for the extracted information, it would also help in the use of an analytical symmetric method such as Kullbach–Leibler (Lee and Seung, 2001) distance in studying the pattern of the UHI over time.

### 4.2. Result of process optimization

The use of the FFT algorithm for increasing the speed of the calculation did help in characterizing the images effectively. But, as described earlier, because this study was dealing with the image with a grid size of 89 × 87, the time and memory consumption required for processing the images were relatively low (around 22 s per image as compared to more than two minutes for processing without the FFT). Even after using the FFT, as the dimension of the images increased, both factors, i.e. time and memory usage, increased exponentially. This might lead to the process of mining consuming more resources. Therefore, there is a need for the development of an even more robust algorithm for the calculation of very large image data set. One option would be to break up the image into subsets and then process them using a parallel
computing environment, merging them together upon completion. In that case, the validity of this process used in this research needs to be examined further.

4.3. Result of visual mining

The LST images were then plotted in a wire frame model to analyze visually their temperature profiles. In this model, the latitude and longitude were projected along the x and y axes, and the temperature values were projected along the z axis, thereby creating a 2.5-D mesh model without volume. This was mainly done because the visualization capability in 2.5 and 3 dimensional models were more than that of the conventional 2-D flat images. The dimension of time was then added to the model bringing all the spatial LST images in accordance with the time series. Care was taken that the daytime and nighttime images were separated accordingly. A series of animations were created to analyze the profiles over time. This aided in interpreting the skin temperature UHI behavior and how it varied from one day to another, within a month, and over the year. This process also aided in studying the resulting images as a whole, since visually analyzing each image independently would be labor intensive.

From Figs. 9 and 10, one can observe the temperature difference. These figures aided in visualizing areas where the heat signatures were relatively higher than their surroundings. These profiles represented the areas with maximum heat signatures potentially forming heat islands. These profiles were evident around the center of the images. More than one such profile (possible heat island) was identified in some images. The model was effective in characterizing the majority of the images and through this process we were able to identify a few images that were not modeled properly due to non-normal distribution of the data.

Two discrete heat islands observed. The major one was located near the city center extending towards the northern part of Marion County and well into Hamilton County. The other was located toward the southern end of Marion County. The heat island in the northern part of the county was distinct compared to the one identified in the southern part of the city. The heat island in the southern part was more visible in the nighttime images than during the daytime images (refer to the area of interest within Figs. 11 and 12). This effect might be attributed to the fact that the northern part of Marion County and parts of Hamilton County have experienced rapid development over the past few years. The measurable presence of the heat island over this region might be attributed to the increase in impervious surfaces due to urban development. The southern part of the county, on the other hand, experienced less expansion and development was mainly industrial and agricultural. These land use types had been demonstrated to consist of less impervious surfaces compared to those with commercial uses. Through the time series animation, a strong variation was observed in the LST around the southern part of Marion County when seasonality was taken into consideration. This effect might be due to that counties south of Marion (i.e. parts of Morgan, Johnson and Shelby) had considerable degree of agricultural land.

There were clear contrasts observed between the UHI and their rural background during the months of June to August. These distinctions were not very noticeable during the early and late winter months. The main reason for this could be due
Fig. 10. The series of images represent the selective frames within the animation depicting the model of the nighttime UHI characterized from the MODIS LST. The images from 1 to 10 are from the month of February to November excluding March. Since no images from the month of March satisfied the maximum cloud criteria the figure shows two results from the month of April instead of one. The images from 1 to 10 are from the following date in that order: 5 February, 9 April, 14 April, 17 May, 17 June, 9 July, 3 August, 4 September, 1 October and 10 November.

Fig. 11. Smoothened daytime LST image of 3 August, 2005, overlaid over the urban class obtained from the 2004 ASTER LULC classification.
to the presence of cloud cover and possible surface wetness caused by rain and snow, leading to improper and inconsistent characterization of the images. Out of the 94 images that were analyzed, a few images were found to have anomalies, i.e. within certain images the UHIs over the rural areas were found to be relatively higher than those in urban areas. The 3-D model helped us analyze the effect of no data on the results. The existence of water increased the emissivity of any material making it difficult to differentiate between the otherwise low-emissivity classes. Despite that emissivity measurements were not provided when the cloud cover is present, the presence of wetness on the surface, due to recent rain or snow melt, would make a difference. Another mitigating factor is that several of the low-emissivity surfaces represent dry areas. For these cover types, night dew would be the primary source of moisture for increased emissivity (Snyder et al., 1998). Cloud cover and periods of rain and snow complicate the visualization of the UHI. This is the main reason for the UHI being more prominent during the summer seasons and with relatively more noise-free images. The problem of monitoring the so developed model for the Marion County is the difficulty of obtaining suitable noise-free images during the winter months. An understanding of these factors would drastically enhance the ability to estimate the amount of uncertainty within the results obtained from this proposed model. In order to do so, further study is needed to analyze the LST images in relation to the weather data estimating the amount of recent dew, rain or snow. From the 3-D model and the animation, it was observed that nighttime images, with 50% or less noise at the regional level, were modeled effectively whereas daytime images with 30% or less cloud cover were modeled effectively. These values hold true for this particular study area and should be tested for other regions.

The UHI patterns were then analyzed with the relationship with land use and cover pattern. The 2004 ASTER based land use/cover classification was used for the analysis. From the list of classes, two main divisions, urban and rural, were made (refer to Table 1). It was observed that most of the maximum temperature regions within the LST were located within the urban location. This result is in agreement with the study carried out by Weng et al. (2006). It found that the center of the UHI was located to the north of the commercial business district. Figs. 11 and 12 illustrate the urban heat signatures with respect to the ASTER land use classes. Since the model performed efficiently for the 94 images, this technique could be easily extended for the analysis of MODIS images for other years using a desktop computing facility. Our future research will involve the extraction of these heat islands as functions so that one can study influencing factors such as wind, type of building, etc. for the temporal variations in the location and spread of the UHIs. Since most of the process was automated, further study is also being directed toward analysis and comparison of the heat islands for other major cities of United States and globally. The technique implemented within this model has found to be effective in characterizing heat islands and efficient in terms of the processing required to identify them.

5. Discussions and conclusion

The MODIS LST images were found to have great potential in monitoring the UHI phenomenon. Three of the main processing difficulties encountered within this research were characterizing the UHI phenomenon as a continuous surface, interoperability and computing capability. The kernel convolution technique was found to be efficient in characterizing the temperature values over space. Other techniques such as variograms and linear parametric models could not be used. The limitations of these models are their failure to adapt to variability, their heterogeneity and the need for human intervention in the processing. In our research, the UHI magnitude represents the relative difference between the mean and maximum temperatures. Even though there was a change in the maximum temperature after kernel convolution, the center and distribution of the UHI was not altered. Nevertheless, the technique of kernel convolution did not completely solve the problem of no data values due to cloud and snow within the images. It did model the data effectively where the percentage of no data values were around 50% or less for the nighttime images and 30% or less for daytime images, at the regional level. These values held true for this particular study area, and but needs to be tested for other regions. Furthermore, the method used was not widely available within the conventional software. Therefore, the model was designed and implemented using open
source software implementing geospatial data acquisition libraries (GDAL). Even though these libraries implement basic spatial analysis capabilities, the developments within these modules are still at an early stage. Most of the problems, over the course of this research, involved handling these minor glitches and resolving them. Since this entire process was automated, it gave added scope for modeling the LST for monitoring of UHIs elsewhere.

Exploratory analysis was found to be effective. The analysis aided in understanding the skin temperature UHI behavior and how it varied monthly and yearly. This process also aided in studying the resulting images as a whole, because visually analyzing each image independently would be time consuming. The heat islands were clear and well separable from their rural background during the months of June to August. This clear distinction was not easily observed during the early and late winter months due to a large number of missing values within the acquired images. The analysis of the characterized UHI, with the land use and land cover, aided in identifying that the center of the UHI was located to the north of the commercial business district and the region with high temperatures concentrated more within urban locations. The process also led to the identification of erroneous images within the series and also aided in visualizing the behavior of the UHI within the study area over time. This method is also being tested for several major American cities, so that patterns can be compared in order to aid in understanding the structure and behavior of the UHI in both space and time. Further research is also in progress for extracting the UHI as a series of Gaussian functions instead of representing them as a series of images.

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