Spatio-temporal modelling and analysis of urban heat islands by using Landsat TM and ETM+ imagery

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In this paper we propose a method for characterizing UHIs by using a non-parametric model. Landsat 5 and 7 images obtained over the city of Indianapolis were used for analysis of UHI over space and time. The images were subjected to kernel convolution implementing Gaussian bi-variate function for non-parametric characterization of the UHI. The convoluted images were then analyzed, for pattern over space and over time. It was found that the spread of the UHI in Indianapolis increased from 13.90 km to 21.63 km in the west-east direction and from 10.98 km to 15.90 km in the north-south direction from 1985 to 2000. The changes in the UHI from 1995 to 2000 were evident in all cardinal directions. The model aided in successfully characterizing UHI in terms of its location, spread, and the rate of increase, facilitating a clearer image of UHI through space and time.

1. Introduction

Anthropogenic change, associated with land cover, appears to be tightly coupled with urban heat. These rapid changes in land use and land cover during recent years have been facilitated, partially by natural, but predominantly by human causes. The extent of land cover and land use change is widely evident within major cities. The type and nature of the human landscape around a city, to satisfy various social and economic needs, has given rise to several phenomena, such as air pollution, water pollution and micro-climate change (Kondratyev and Varotsos 1995, Varotsos et al. 2005). Apart from these, the urban city centres also tend to have higher solar radiation absorption and greater thermal capacity and conductivity (Weng 2001). These changes are mainly a result of a sudden increase in the area of impervious surfaces within the city, in contrast to its hinterland. This difference in temperature between the urban and rural areas is called the urban heat island (UHI). The presence of UHIs has been studied and documented for New York (Jin et al. 2005), Houston (Streutker 2003), Phoenix (Hawkins et al. 2003), Indianapolis (Weng et al. 2004), Guangzhou (Weng 2003), Beijing (Jin et al. 2005), Seoul (Kim and Baik 2005), Athens (Katsoulis and Theoharatos 1985) and other cities. The study of UHIs is relevant pertaining to its relationship with differences in temperature, but also acts as one of the major factors influencing other phenomena, such as impact on natural ventilation (Ghiaus et al. 2006) and urban meteorology (Khan and Simpson 2001).

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Studies have shown that the UHI has a strong influence on weather, leading to anomalies in rainfall patterns and lightning (Shepherd and Burian 2003). The UHI is also a factor in the assessment of the role of air-conditioning systems, impact on human health and environmental conditions (Masson 2006).

Previous studies have examined the UHI phenomenon using both ground-based and remote sensors. Fast et al. (2005) used temperature data loggers to track the thermal changes over the city of Phoenix, Arizona, whereas Jung et al. (2005) used airborne hyperspectral images to study the effect in Hungarian villages. Kato and Yamaguchi (2005) studied the heat balance during the day time and also the night time temperature, using Landsat enhanced thematic mapper (ETM+) and advanced spaceborne thermal emission and reflection radiometer (ASTER) images. Stathopoulou et al. (2004) analysed the presence of the UHI using the advanced very high resolution radiometer (AVHRR) sensor on board the National Oceanic and Atmospheric Administration (NOAA) satellite. Rajasekar and Weng (2009) analysed the change in UHI patterns over the year using moderate resolution imaging spectroradiometer (MODIS) images. Voogt and Oke (1998) analysed the effect of surface geometry on temperature. Weng (2003) analysed the relationship between land cover and urban heat islands using fractals. Weng et al. (2006) developed sub-pixel quantitative urban surface biophysical descriptors and related them to land surface temperature variations. Atkinson (2003) defined a numerical model of UHI intensity. Streutker (2002) estimated the centre and spread of the UHI using a parametric model.

There has been considerable research conducted on UHIs, yet it remains difficult to generalize the magnitude, location and spatial distribution of the UHI for several reasons. These reasons include the shape, the extent of the city, the layout, the type and material of the surrounding areas and the resolution of imagery used to characterise the phenomenon. These factors not only affect the spatial extent of the UHI, but they also affect its magnitude. Over the years, statisticians have developed several methods of generalization to compensate for the issue of characterizing the surface in the spatial domain. While various approaches of kriging and thin plate spline models have been used 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. This failure to adapt to 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 (Paciorek and Schervish 2006). Lastly, a single parametric model could be used for the analysis of a single image; however, it becomes difficult to apply this over multi-temporal and multi-sensor images in order to conduct a successful comparative analysis. This aspect gets further complicated due to the changing nature of the land cover and land use, and also the fuzziness involved within the boundary between the urban and rural areas.

The main objectives of this study are three-fold. First, to develop a generation method using a non-parametric model to characterise the UHI from the Landsat images. Second, to extract statistical parameters, such as centre, spread, minimum temperature, maximum temperature, magnitude, etc., from the characterized images. Third, to analyse and compare statistical parameters extracted from the time series images to study the change in the UHI in relation to the change in land use and land cover.
2. Study area and data

Indianapolis/Marion County, Indiana, USA, was chosen as the study area. It possesses several advantages that make this city an appropriate choice for such a study. Indianapolis has a single central city. The city is located on a flat plain and is relatively symmetrical, having possibilities of expansion in all directions. Like many other American cities, Indianapolis, over the past decade, has been rapidly increasing in population and in area. According to the US census bureau, the population of Indianapolis in 1980, 1990 and 2000 were 700,807, 731,327 and 781,870, respectively. The need for space to accommodate this increase in population has led to areal expansion through encroachment into the adjacent agricultural and non-urban lands. 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. These characteristics make Indianapolis an ideal study area for the spatial and temporal change of UHI. Figure 1 shows the study area and its environment.

Extracting information of land cover from satellite images allows for monitoring urban changes over time (Weng et al. 2004). There was not sufficient ground-based thermal sensor data available for the time period under study; as a result, Landsat thematic mapper (TM) and ETM+ images were used. Landsat data is available at medium resolution, which is a suitable choice for analysing the spatial change over a long period of time. The TM sensors onboard Landsats were specifically designed for quantitative analysis of the Earth’s land surfaces (Vogelmann et al. 2001). Furthermore, since the spectral window of Landsat TM and ETM+ are of similar ranges (10.4 to 12.5 μm), it makes Landsat images the best available resource for this study of UHIs over Indianapolis in space and over time. A total of three images, two from Landsat TM (23 July 1985 and 3 July 1995) and one from Landsat ETM+ (22 June 2000) were used for the analysis. All the images were selected during similar

![Figure 1. Study area and its environment.](image-url)
seasonal times in order to reduce the seasonal variability between images and also to use the vegetation to differentiate urban from rural settings. For each image, the amount of cloud cover was less than 10%.

3. Method

The scheme describing the method of characterizing UHI over space and time is shown in figure 2. A detailed description of the major steps undertaken are presented in the subsequent subsections.

3.1 Geometric correction

The obtained Landsat images were of correction level ‘systematic’. Therefore, the geometric corrections of all the images (Landsat-5 and Landsat-7) were carried out based on image to image geo-rectification. A geometrically pre-corrected and verified Level 1b ASTER image was used as a base image for the correction of individual time series images. A range of 20 to 30 sample points was selected, based on field studies for every image, with respect to the ASTER imagery and were used for geo-rectification. Once rectified, the thermal infrared band (TIR) was resampled from 90 to 120 m resolution. This was carried out to bring the images to similar resolution, i.e. to the spatial resolution of the TIR band of Landsat-5. The results of the geometric corrections had a relative root mean square error (RMSE) of less than 0.3 of a pixel, which was well under half a pixel.

3.2 Radiometric normalization

There are several different radiometric correction methods available. Choosing the right method for our study was based on the available data and the task at hand. There are two most commonly used techniques, absolute radiometric calibrations and relative radiometric calibrations. Since the context of the study is to analyse the

Figure 2. Flow chart describing the method implemented within this study.
UHI effect for the same area from time series images, we preferred the use of relative radiometric calibration over absolute normalization. The selection of pseudo invariant features (PIF) in all the images became another important task within the relative radiometric calibration process. Multivariate-alteration detection (MAD) (Schroeder et al. 2006), post-correction evaluation index (quadratic difference index) (Paolini et al. 2006) and a statistical selection of features using principle component analysis (Du et al. 2002) are some examples of the methods available. Some of them depend on the field data and others purely depend on statistical models. In our study, based on our earlier field data and knowledge of the study area, we decided to implement a semi-statistical approach (Haute 1988) using temporally invariant features (Chen et al. 2005).

Radiometric normalization of these images was accomplished by converting to exoatmospheric radiance or black body temperature. The digital number (DN) values of the Landsat-5 and Landsat-7 TIR band were converted from their sensor-recorded DN to spectral radiance using equations (1) (Markham and Barker 1985) and (2) (NASA 2007), respectively:

\[ L_\lambda = 0.0056322 \text{DN} + 0.1238 \]  
and

\[ L_\lambda = 0.0370588 \text{DN} + 3.2. \]

The spectral radiance of the TIR bands were then converted into blackbody temperature using equation (3) (Wukelic et al. 1989):

\[ T_B = K_2 / \ln(K_1 / L_\lambda + 1), \]

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

After the conversion of the images to blackbody temperatures, time-invariant features (TIFs) between images were selected for normalization. Within this study, selection of the TIFs were based on previous field surveys, available building history and visual examination of the true colour and pseudo true colour images over time. A total of 77 distinct locations, containing both minimum and maximum land surface temperature (LST) ranges were selected. Care was taken that the selected points consist of samples from both the maximum and minimum temperature ranges.

A 2000 Landsat-5 image was selected to be the reference image. The remaining two images were relatively corrected to this image. The main rationale for selecting the 2000 image is the availability of other geo-spatial information such as ASTER imagery from 2000, temperature characteristics and ASTER-derived land cover classification at 15 m level for the same period. Furthermore, the 2000 image was from Landsat-7, with relatively high (90 m) spatial resolution; therefore, the spatial accuracy of this image was assumed to be greater than the remaining images.

The land use land cover (LULC) data was developed from the ASTER 2000 image using a semi-automatic technique. An unsupervised classification method (iterative self-organizing data analysis) was chosen to classify the ASTER data, with a maximum iteration of 30. A total of 120 clusters were created and labelled in
reference to 2003 and 2005 aerial photos. Reclassification was then executed for the fuzzy regions. Post-classification smoothing and image refinement were also conducted to improve the accuracy of image classification. Classification accuracy for each image was assessed against the 2003 county aerial photo. A stratified random sampling method was applied to choose 50 samples in every LULC category. The overall accuracy was above 85%. For a detailed description of the method implemented and the results acquired, see Liu and Weng (2008). Figure 3 shows the LULC map of seven classes (excluding the background). In the final classification of Marion County (the study area), the class ‘wetlands’ was not present, so it was removed and is therefore not visible in table 1.

The final process involved the extraction of the brightness component (temperature values at TIF locations) from the reference and subject images. The reference and subject image values for the same locations are now being examined for the degree of linear association by means of linear regression analysis (Wilks

Table 1. 2000 LULC classification and their corresponding spectral emissivity.

<table>
<thead>
<tr>
<th>Class</th>
<th>LULC type</th>
<th>Spectral emissivity assigned</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Impervious surfaces</td>
<td>0.966</td>
</tr>
<tr>
<td>2</td>
<td>Barren lands</td>
<td>0.977</td>
</tr>
<tr>
<td>3</td>
<td>Grass lands</td>
<td>0.972</td>
</tr>
<tr>
<td>4</td>
<td>Agriculture</td>
<td>0.973</td>
</tr>
<tr>
<td>5</td>
<td>Forest land</td>
<td>0.987</td>
</tr>
<tr>
<td>6</td>
<td>Water</td>
<td>0.991</td>
</tr>
</tbody>
</table>
1995). A linear regression equation is tested for the data pair. Using the method of least squares, the regression equations are:

\[ y = 0.771x + 62.51 \text{ (for 1985−2000)} \]  

(4)

and

\[ y = 0.5195x + 134.08 \text{ (for 1995−2000)}. \]  

(5)

The coefficients of determination, \( R^2 \), (Chattopadhyay and Chattopadhyay-Bandyopadhyay 2008) for the above equations are 0.9127 and 0.9136, respectively, and such high values reflect the high degree of linearity between the predictor and the predictands. A scatter plot is presented in figure 4, where an obvious linear pattern is apparent. The equations generated above have been used to convert the subject images to be radiometrically similar to that of the reference image.

3.3 The non-parametric model

This subsection is a modification from the paper by Higdon (2002). 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 process convolution model was extended by the authors to model the UHI as a two-dimensional Gaussian process. 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 successively increasing the density of the lattice by a factor of two in each dimension and reducing the variance of the variates by a factor of \( 2^d \), which leads to a continuous Gaussian white noise process over \( R^d \). White noise is a (univariate or multivariate) discrete-time stochastic process whose terms are independent and identically distributed, all with zero mean. Gaussian white noise is white noise with a normal distribution. The convolution of this process can be equivalently defined using a covariogram in \( R^d \). 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.

For example, let us assume that \( y_{(1,1)}, \ldots, y_{(i,j)} \) (where \( y \) is a two dimensional matrix of \((1,1),\ldots,(i,j)\)) are data recorded over the two-dimensional spatial locations \( s_{(1,1)}, \ldots, s_{(i,j)} \) in \( s \), a spatial process \( z=(z_{(1,1)}, \ldots, z_{(i,j)})^T \) and Gaussian white noise \( e=(e_{(1,1)}, \ldots, e_{(i,j)})^T \), with variance \( \sigma^2_e \). In this research, the spatial method represents the data as the sum of an overall mean \( \mu \).

\[ y = s + z + e, \]  

(6)

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 non-zero at the two-dimensional spatial sites \( \omega_{(1,1)}, \ldots, \omega_{(a,b)} \), also in \( s \) and \( x=(x_{(1,1)}, \ldots, x_{(a,b)})^T \) is defined, where \( x_{(1,1)}, \ldots, x_{(a,b)} \) are independent draws from an \( N(0,\sigma^2_{\omega}) \) distribution. The resulting continuous Gaussian process is then:
where $k(\cdot - \omega_p)$ is a kernel centred at $\omega_p$. This gives a linear model:
\[ y = \mu l_{(i,j)} + Kx + \varepsilon, \quad (8) \]

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

\[ K_{pq} = k(s_p - \omega_q)x_{pq}, \quad (9) \]

\[ x \sim N(0, \sigma^2x l(a, b)) \quad (10) \]

and

\[ \varepsilon \sim N(0, \sigma^2x l(i, j)). \quad (11) \]

The results of this model were then analysed for patterns over space and time. The comparison was based on the UHI centre and the spread of the UHI over space and time. The results of the kernel convolution were first compared using two-dimensional (planar) and three-dimensional (mesh) models. Then, the heat island was characterized as the phenomenon with temperature above the mean temperature of the respective image. In order to achieve this, only the values above mean temperature were considered for further analysis in this research. This process aided in the removal of negative heat islands (areas where the temperature is much less than the mean temperature due to the specific nature of the land cover). The heat contours were then generated from each image. The assumption at this stage is that all the images were relatively corrected, and therefore the temperature contours should be comparable. The increase or decrease in the size of each contour would indicate the extent of positive/negative change in the UHI over time.

4. Results

4.1 Sensitivity analysis

As described in equation (8), the smoothing kernel, or the parameter that defines the degree of smoothing, is very important. One can also note that, as the degree of smoothing is inversely proportional to the smoothing kernel, i.e. as the value of the smoothing kernel decreases, the degree of smoothing over the spatial domain increases. Within the model, the degree of smoothing is maximum at ‘1’, leading to a kernel-convoluted image, whose values are equivalent to the mean of the original image. The degree of smoothing is minimum (or zero smoothing) when the smoothing parameter is equal to ‘0’. In this case, the final kernel-convoluted image is the same as that of the original image. Within our study, the selection of appropriate smoothing parameters that would best describe the phenomenon under study was a challenging task. Before arriving at final values, a sensitivity analysis was performed with various smoothing parameters and a sample image (year 2000 image). The results obtained from the sensitivity analysis are illustrated in figure 5.

From the results obtained by the various simulations, the smoothing value of 0.5 (see equations (6), (7) and (8)) was selected to be the most appropriate for this study. With this smoothing parameter, the number of heat islands that were characterized was minimal. The focus of this study was to understand the development and spread of the UHI over the entire city. The minimum number would clarify effective comparisons of the city as a whole, rather than small regions with minor variations, leading to a global model for the city of Indianapolis. At the same time, care was also
taken that over-smoothing did not occur. The selected smoothing parameter (0.5) was then used to characterize remaining images.

4.2 Characterizing UHIs

The image statistics describing minimum, maximum and mean temperatures before and after kernel convolution are given in table 2. The statistics of the images before convolution show a strong variation between minimum–maximum and mean–maximum temperatures. These variations are attributed to outliers present within the LULC. These outliers are the result of certain LULC within Marion County, radiating either very high or very low temperatures. The process of kernel convolution aided in reducing the effect of these outliers and characterizing the temperature within Marion County as a process (see figure 6, which shows the result of the image before and after convolution). The results from the images after the kernel convolution are uniform within the analysed time series. The change in temperature within the time series images were in the range of 0.5–2.0°C, with a constant increase in the temperature from 1985 to 2000. The city’s development is highly correlated to this increase in temperature leading to an increased UHI effect.

Since the main aim of this research was to analyse the UHI effect within Indianapolis city, it becomes important to differentiate between the urban and rural regions. In the domain of image classification algorithms, there has been a range of studies aimed at implementing varying methods to differentiate between urban and

Table 2. Description of the image statistics before and after kernel convolution. All temperature values are in K.

<table>
<thead>
<tr>
<th>Image statistics</th>
<th>Before</th>
<th>After</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Minimum</td>
<td>Maximum</td>
</tr>
<tr>
<td>Date</td>
<td></td>
<td></td>
</tr>
<tr>
<td>23 July 1985</td>
<td>263.9</td>
<td>302.23</td>
</tr>
<tr>
<td>3 July 1995</td>
<td>275.86</td>
<td>304.79</td>
</tr>
<tr>
<td>22 June 2000</td>
<td>283.14</td>
<td>303.62</td>
</tr>
</tbody>
</table>

Figure 5. Result of the sensitivity analysis performed over Landsat-7 (year 2000) imagery. From (a) to (h), the smoothing parameter ranges from 0.1–0.9.
rural environments. Some of these methods are based on manual methods, and some are based on statistical approaches. In spite of several semantic descriptions of urban and rural areas, the boundary between them remains fuzzy. More often, the development of mixed land use, e.g. residential housing areas around agricultural areas, has led the relationship between the urban and rural regions to be both fuzzy and disjoint. In this study, to perform the initial analysis, we adapted a novel approach of using the mean temperature value as an indicator for differentiating the urban environment from its surrounding rural environment. The process involved separating the image into two regions. One class includes the regions equal to and above the mean value and the other includes the regions below the mean values. This method was more appropriate to our model because, through the process of kernel convolution, the mean temperature of the image is retained, while the variates of the variance are varied. In the new image, the regions below the mean temperature were assigned a uniform value equivalent to that of the mean temperature of that particular image. The temperature values of the remaining region were retained. This process further facilitated that the study would remain towards the analysis of the positive UHI effect.

Figure 7 shows the UHIs of time 1985, 1995 and 2000. From the structure of the temperature values within the study area, we can infer that the northern and southern part of Indianapolis have undergone considerable increase in the surface temperature over the selected years. Furthermore, we were able to infer that the rate of change of temperature from the city centre towards the rural background is gradual in the case of 1995 and 2000 images and this rate of change is steep in the case of the 1985 image. One of the main reasons for this effect is the change in land use and land cover over these selected time periods. The mixed developments within the rural areas have also contributed to the overall increase in temperature around rural areas, contributing to the slope of the heat island decreasing over time. This difference is very strong between 1985 and 1995, compared to the 1995 and 2000 images. This demonstrates that the rate of change of urban heat from its centre to its periphery is directly proportional to the rate of development/urbanization (impervious surfaces) in the case of Indianapolis.
4.3 Space–time analysis of the UHI

The characterized surface temperature image was then converted into contour lines. These lines were analysed with respect to each other and with respect to false colour composite (FCC) images using bands 4–3–2. From the analysis of the independent contour line (see figure 8(a)), we can visualize the change in the concentration of heat (relative radiometric temperature profiles) with respect to time. Over the 5 year period from 1995 to 2000, the UHI around central Indianapolis has increased in both its size and spread. During the 15 year period, 1985 to 2000, the spread increased 7.7 km in the east–west direction and 5 km in the north–south direction. This increase could be attributed to several reasons, such as reduction in the amount of canopies, change in land cover and change in land use. This increase in the spread of the UHI also coincides with the fact that the population of Indianapolis has increased from 700,807 in 1980 to 781,870 in 2000, an increase of more than 10% in 20 years. On comparing the centre of the UHIs, we were able to identify a modest shift of 0.3 km towards the northwest direction from 1985 to 1995. There is also a minimal shift of 1 km towards the east from 1995 to 2000 (see figure 8(b)) because the development of Indianapolis as a city has been occurring in cardinal directions. This LULC change in directions may not be the same in terms of the increase in impervious surface area, but contribute similar amounts of thermal radiation generated. For example, slow development of industrial areas around the south, and fast development of commercial and residential areas around the north contribute comparable amounts of thermal radiation. Based on the current study, the
movement of the centre of the UHI is detected as being directed towards the northeast. Nevertheless, a future study, incorporating the same model but involving the analysis of 2005 and 2007 images, would shed more light into the movement of the UHI over time.

From the overlay analysis of the contour lines over the FCC (see figure 9), we observed that the characteristic shape of the UHI is strongly correlated with the location and distribution of impervious surfaces. There were few changes (except for an overall increase in the temperature) in the pattern of the UHI around the city centre due to the fact that the city centre has not undergone much change over the 15 year period from 1985 to 2000. However, changes in pattern, especially spread, were evident around the periphery of the heat island. These outer rings were more biased towards the west due to the urbanization at the northwest part of Indianapolis adjacent to the highway (I-486).

From figures 9(a) and (b), we can infer that the UHI is spread unevenly from the central business district. During the period from 1985 to 1995, the city of Indianapolis started to spread around the south and north with more concentration in the northeast. These developments were mainly residential. From the FCC, one can also visualize that the area of impervious surfaces (cyan in the figure) around the northeast corner of the city has increased in the 1995 image in comparison with the 1985 image. This development, and its influence on the UHI, have continued beyond 2000, and is evident from the figure 9(c). The change in the UHI within this 5 year period (from 1995 to 2000) is more evident in all the directions (east, west, south, northeast and northwest). Apart from urbanization, figure 9(c) also shows the influence of the type of land cover on the UHI pattern. In spite of considerable development around the north-western part of Indianapolis, this region is highly influenced by the lake and the dense canopies of the semi-forested areas. For the period 1995 to 2000, increases in impervious surfaces had no significant change in the mean heat around this region. This might also be due to the structure and shape of the development that took place. A detailed understanding of this might shed

Figure 8. (a) Comparison of the UHI centres over time and (b) the change in the size of the UHI core from 1985 to 2000, illustrated with an example of a constant temperature ring of 20°C.
more light towards understanding the nature of developments that might contribute to less thermal radiation.

Overall, the model aided in closing the gap within current research by providing a method to analyse UHIs effectively from multi-sensor multi-temporal images in both space and time. The characterization of the UHI through a non-parametric kernel convolution model using fast Fourier transforms, rather than the conventional parametric model, facilitated efficient analysis. Furthermore, this model could also aid in the analysis of multiple images from Landsat and other similar sensor images with minimal human intervention. This model, if extended further, could be very useful for comparing the change in urban heat patterns over time, not just for one city, but also be helpful in comparing between major developed and developing cities around the USA and the rest of the world.

Figure 9. Overlay analysis of characterized UHI pattern over the FCC of Landsat images: (a) 1985, (b) 1995 and (c) 2000.
5. Conclusions

The problems of characterizing and modelling UHIs over space and time still exist. Parametric modelling may be helpful in characterizing the UHI over space. However, parametric models do not prove to be efficient while characterizing the same phenomenon over different space and/or over varying temporal resolution. In order to address this issue, the present research developed a non-parametric model for analysing the behaviour of the UHI in space and time using Landsat TM and Landsat ETM images. Non-parametric analysis using kernel convolution was explored to characterize the phenomenon over space. Furthermore, with the advancement in the field of spatial analysis, techniques such as three-dimensional visualization and overlay analysis were explored to analyse the effect over time. Through this research, a synergic merger model for UHI pattern extraction and analysis from Landsat-5 and 7 images was conceptualized and developed.

Landsat-5 images from the year 1985 and 1995, together with Landsat-7 images of the year 2000, covering the city of Indianapolis, USA, were used to test the conceptual model. The images were processed for relative radiometric correction in order to facilitate comparison and analysis. The images were then characterized into a continuous surface using the kernel convolution technique. In order to arrive at the best smoothing parameter, a sensitivity analysis was performed using the 2000 image. From the results of this analysis, a smoothing parameter of value 0.5 was selected and was used to characterize the rest of the images.

The characterized images were then analysed for change over time using visualization and overlay techniques. It was found that the spread of UHIs increased from 7.7 km in the x direction and from 5 km in the y direction for the 1985 and 2000 images. The increase in the spread of the UHI coincided with the increase in population from 700,807 in 1980 to 781,870 in 2000 (an increase of more than 10% in 20 years time). On comparing the centre of the UHI, we were able to identify a modest shift of 0.3 km towards the northwest direction from 1985 to 1995, and a shift of 1 km towards the east from 1995 to 2000. The rate of urbanization and its direction were evident by analysing the UHI contour map in conjunction with the false colour composite image using bands 4–3–2 and ASTER derived LULC for the year 2000. It was found that the rate of development has been even around Indianapolis, with concentration at the north and south ends of the city over the years 1985 to 2000. It was also found that land cover played a vital part in thermal behaviour. A well-balanced land cover, consisting of forests, water bodies and impervious surfaces tends to radiate less heat in comparison with uneven distributions of these. However, this effect may also be due to the shape or the structure of urban development. An in-depth analysis into this is needed to come to a definite conclusion. The heat contours not only defined the UHI, but could also be used for differentiating the urban and rural boundary. This boundary map could be made crisp or fuzzy by using different temperatures as a parameter in conjunction with a land use and land cover map.

Landsat has much potential for providing good time series images of the major cities around the world from 1985 onwards. Furthermore, other products that are generated from it could be used for the further understanding of the behaviour of the phenomenon under study. This model could also be improved and extended for spatio-temporal analysis using other images, such as ASTER, and for studying the phenomenon for other major cities of the world. The developed model is very promising for data mining and analysing the spatio-temporal characteristics of the
UHI. It would help the researchers to answer questions such as the effect of temporal resolution in the monitoring of UHI, the areas within a city causing major impacts and how LULC affects the nature and spread of the UHI. Furthermore, there have been studies that have demonstrated that the UHI effect has a strong impact on energy needs, climate, biodiversity, residential water use, etc. The results of this study will be useful to researchers within the above-mentioned domains. The results from this proposed model could be used as an input to some of the climate and energy utilization models in order to study the cause and effect relationship between these phenomena. The combined results of the models could aid urban planners and environmental managers in understanding the effect of land use and land cover on the thermal radiation around cities.

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