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# Spatial analysis of the Surface Urban Heat Island

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## ABSTRACT

In this paper, we present a novel framework to characterize the complex spatial structure of the intra-urban heat island. Cities are known to be warmer than its surrounding areas because of the Urban Heat Island (UHI) phenomenon. However, due to the diverse and complex spatial geometries of cities themselves, the temperatures within vary widely. We take advantage of the well-established notion of fractal properties of cities, to characterize the complex structure of these hotspots. As a demonstrative case study, Land Surface Temperatures (LST) for Atlanta, GA, derived from Landsat 8 is used. From clustering analysis at multiple thermal thresholds, we show that the hotspots can be described as a case of percolating clusters. By comparing the area-perimeter fractal dimension at these thresholds, we find these clusters to be statistically self-similar. Furthermore, at the percolation threshold, the cluster size distribution is found to follow a power-law size distribution; and at a higher threshold, deviation from the power law is observed in the form of exponential tempering. We argue that the spatial distribution of the hotspots itself plays a significant role in the overall UHI and fractal analysis techniques lend themselves aptly to the characterization of the same. This has several further applications, such as targeted heat mitigation, assessment of health impacts, and energy load estimation.

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**Keywords:** Surface Urban Heat Island, Land Surface Temperature, Landsat, Fractal analysis, Power law, Self-similarity, Atlanta

## 1. INTRODUCTION

The Urban Heat Island (UHI) effect, is one of the major challenges of intensive urbanization.[1] UHI is the phenomenon of cities tending to be warmer on an average than their non-urban surroundings. This is due to an increase in heat sources and a scarcity of thermal sinks.[2,3] Furthermore, the UHI interacts synergistically with mesoscale heat waves to amplify local heat stress.[4] As a result, UHI contributes to an increase in ailments such as energy demand, heat stress, and even heat-related deaths.[5] The UHI Intensity is, in practice, quantified as the difference between average non-urban air temperature and a representative urban air temperature, such as mean or maximum observed temperature. However, such an approach fails to recognize the spatial heterogeneity that arises within urban areas due to their form and function.[6] To capture the same, in recent times, use of remotely sensed data has gained popularity.[7] While it must be noted that the thermal remote sensors observe the Land Surface Temperatures (LST). As a result, the difference between urban and rural surface temperatures are used to characterize the Surface Urban Heat Island (SUHI). But it provides a unique opportunity to capture the spatial variability of urban temperatures at a higher resolution than the in-situ observations can provide.[8] Furthermore, it also offers a consistent suite of observations across cities of the world enabling comparative studies at a global scale.[9,10]

The UHI is a result of urban form and function. Urban form, such as excess built-up area and lack of vegetation results in reduced heat dissipation. The concrete absorbs solar radiation during the day and dissipates it during the night, resulting in excess heat.[2] Moreover, urban functions such as air-conditioning and vehicular emissions

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also contribute to the same. Notable differences in both urban form and functions across different cities act as an obstacle to the transfer of knowledge across cities and to studies at other spatial scales. However, similar fundamental properties that have been found across diverse cities can be useful here. Cities exhibit self-similar, fractal characteristics in terms of physical assets, such as built-up areas, or building density distribution.[11–13] Furthermore, urban infrastructure networks, such as roads, water supply and drainage pipes and electricity grids, also exhibit self-similar scaling.[14–16] So do the urban metabolic functions such as mobility, traffic, economy, and energy use.[17–19] Building on the fractal morphology of cities, we hypothesize that the resultant SUHI patterns exhibit a fractal spatial structure as well. In intra-city studies, the correlation of temperatures and urban morphology is now well established;[6,20–22] however, the scaling properties of intra-urban heat island (referred to as hotspots in this paper) within cities have not yet been established. As an attempt to bridge that gap, here, we demonstrate a framework for evaluating self-similarity within SUHIs using remotely sensed LST data.

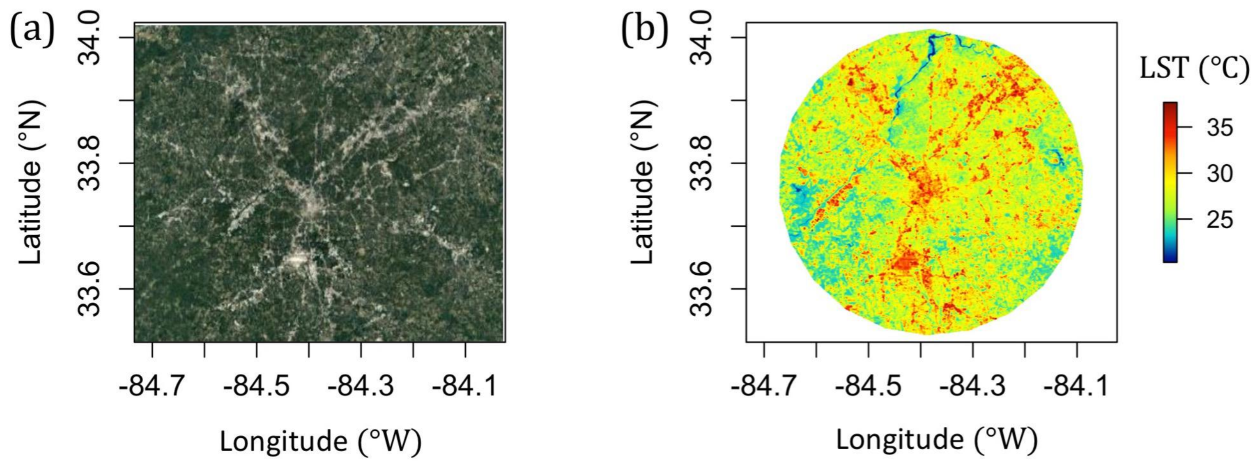


Figure 1. (a) Satellite image of Atlanta, GA obtained from Google Earth Engine (b) Land Surface Temperature map of the same on May 6th, 2014 derived from Landsat 8 shows Atlanta's Surface Urban Heat Island.

## 2. DATA AND METHODS

### 2.1 Land Surface Temperature data

As a case study, the city of Atlanta, Georgia, is selected (figure 1a). Atlanta is the capital and the most populous city of the U.S. state of Georgia with a population of over 5 million people in the metropolitan region. Located in the humid subtropical climate zone (cfa) according to the Koppen Geiger climate classification,[23] Atlanta is often affected by extreme heat, due to both UHI,[24] and recurrent heat waves.[25] As a result, numerous studies have focused on understanding and better characterizing Atlanta's UHI patterns.[24–26] Land surface temperature (LST) data from Landsat 8 (at 90 m resolution) for the city was derived using Google Earth Engine for a cloud-free day of May[27,28] (figure 1b). Methods developed here also enable comparing cities across the world minimizing the difficulties of maintaining uniformity of data quality.

### 2.2 Spatial metrics for fractal surfaces

The UHI is an island of higher urban temperatures in a background of lower non-urban temperatures. As an extension of the same analogy, we conceptualize the LST map as a Digital Elevation Model (DEM) of temperatures. We estimated temperature percentiles, above several thermal thresholds to form clusters of areas hotter than the threshold (as illustrated in figure 2). The identified clusters comprised a set of connected pixels whose temperatures were above the selected threshold (figure 3a). A Moore neighborhood (including diagonals) was chosen for defining adjacencies among pixels. Characterization of scaling properties of topographical surfaces (such as a DEM) as iso-lines has a long history in the field of percolation theory, which is a canonical branch

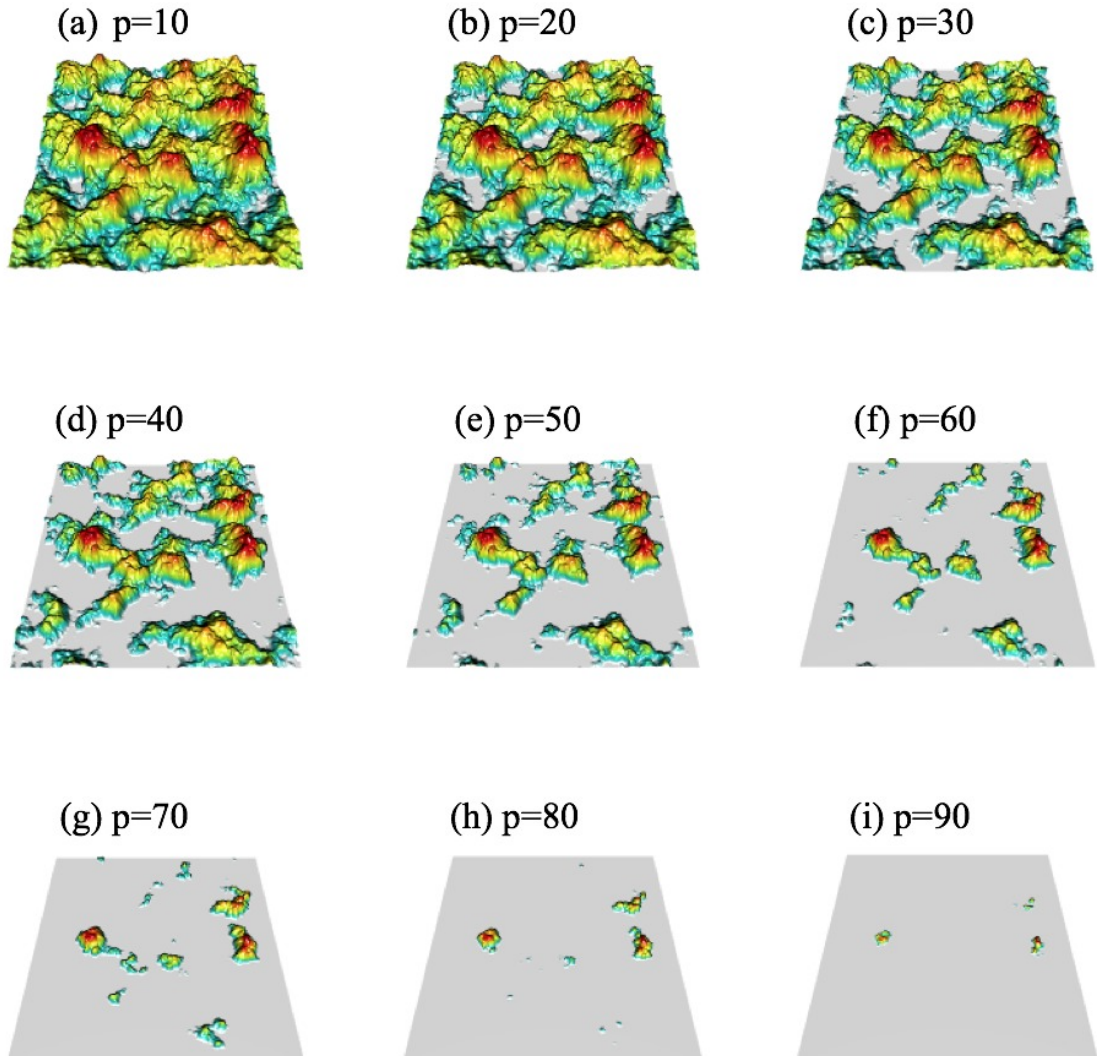


Figure 2. Illustrated above is an example of thresholding by percentile. The thermal maps are represented as 3-d elevation maps where height, as well as color, corresponds to a higher temperature. For each percentile of the thermal threshold, the areas above that are selected, and connected pixels (by Moore neighborhood) are grouped into a cluster. Figures (a-i) show the clusters that emerge above 9 incremental percentiles (shown as p).

of statistical physics that focuses on connected clusters.[29,30] We utilize two tools to test for self-similarity: Area-Perimeter Fractal Dimension of heat clusters and their Size-Distribution.

Area-Perimeter Fractal Dimension (D) is estimated as the exponent of power-law relationships between the cluster area (A) and perimeter (P) via the relationship $P \propto A^{\frac{D}{2}}$.[31] Note that for a system of clusters, the aggregated area-perimeter is used. Isichenko (1992) established that the fractal dimension of a set of topographical iso-lines for a variety of fractal landscapes lies between 1 and 1.75 depending on roughness. Within this, for random site percolation, a D of 1.33 (4/3) is expected of a system of uncorrelated clusters and values above that as spatial correlation increases.[32,33]

For fractal iso-lines, the cluster areas follow a probability distribution with a power-law tail.[32,34] This was first presented as an empirical rule by physicist and geographer Jaromir Korcak, who suggested a general scaling law describing the size-distribution of various geographical objects, including lakes and islands.[35] In summary, this law is expressed as the relative number of islands with an area equal to $a$ is given by the power-law: $N(a) \propto a^{(-\beta)}$. Multiple studies have reported the occurrence of such scaling in natural topography such as islands,[31] lakes,[36] where the respective size distributions are well described by a power-law tail. In hydrology, the area exceedance for flow accumulation is a well-established signature of self-organization.[37] Above the percolation threshold, deviations from the power-law result in some form of tempering. We define the percolation threshold as the temperature at which the number of clusters is maximum. Scaling of the hotspot areas was examined using the exceedance probability distributions, at the percolation threshold and at regular quantiles of temperature above that threshold. Power-law tails were fit to the resultant distributions using a combination of maximum-likelihood fitting methods with goodness-of-fit tests based on the Kolmogorov-Smirnov (KS) statistic and likelihood ratios.[38]

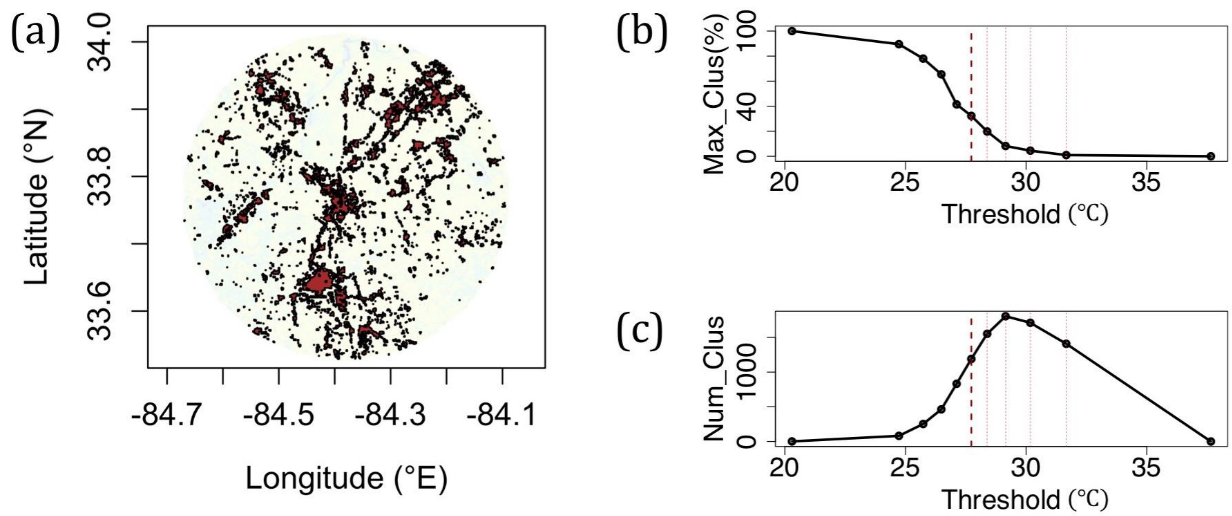


Figure 3. (a) Clusters of high heat (hotspots) above the percolation threshold (31°C) as indicated in red. (b) Size of the biggest hotspot is shown as a percentage of total domain area (c) Number of hotspots is shown for each thermal threshold. In (b) and (c), red vertical lines correspond to 50th, 60th, 70th, 80th, and 90th percentiles respectively. Note that the maximum number of clusters is obtained at the 70th percentile.

## 3. RESULTS AND DISCUSSIONS

### 3.1 Fractal dimension

For multiple percentiles of thermal thresholds (50th, 60th, 70th, 80th, 90th, and 95th), net hotspot areas and perimeters are calculated. Assuming the limiting case of a circular cluster to calculate the proportionality constant, the following equation is used to estimate D:

$$\Sigma P = 0.55 \cdot \Sigma A^{\frac{D}{2}} \tag{1}$$

D is found to be the same for all thresholds tested (figure 4a). This demonstrates statistical self-similarity within each thermal landscape and shows empirically that SUHI has a fractal topography. The fractal dimension is a measure of compactness or sprawl of the thermal hotspots as a whole. Smaller D values indicate that the hotspots are clumped together, possibly even resulting in a single dominant cluster, while larger values suggest a more heterogeneous spread of hotspots (sources) surrounded by cooler regions (sinks). Comparing the D value reported for other aspects of urban form and function, we find the correlation between morphology and temperature to emerge clearly. For instance, Makse et al (1998) reported the fractal dimension of modeled urban clusters to fall within 1.2 to 1.4, with a value of 1.38 indicating the presence of spatial correlations across percolation clusters.[13] Therefore, correlated percolation could be a more suitable model for thermal clusters.

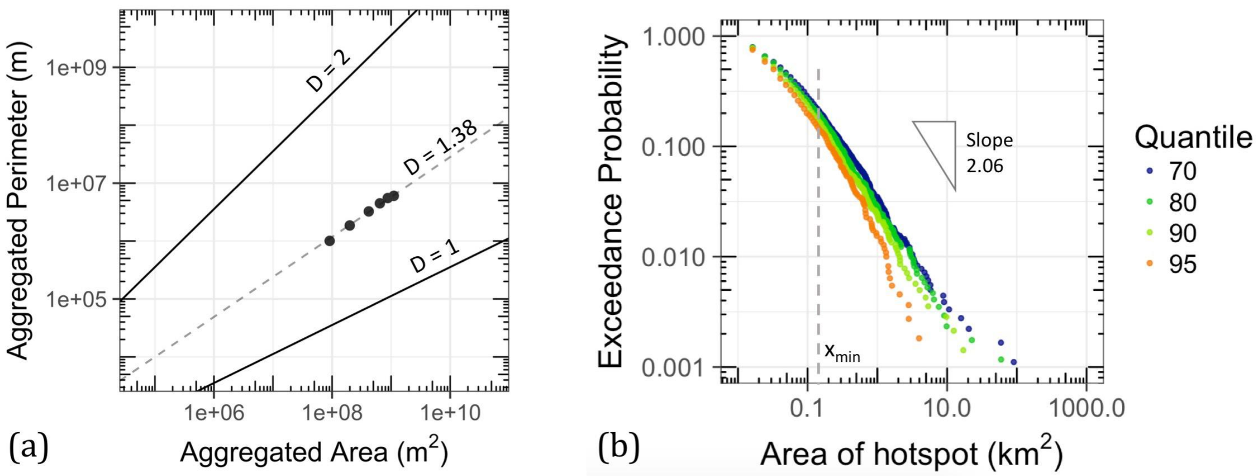


Figure 4. (a) Scatter plot of the aggregated perimeters of the hotspots versus their aggregated areas for 60, 70, 80, 90, and 95th percentiles respectively (from left to right). The fractal dimension (D) is the slope of the line between each point in this graph and a constant intercept k=0.55 that is calculated for a circular cluster. The grey, dashed line indicates the calculated D = 1.38. Additionally, the fractal dimensions of the perimeter of a circle (D =1) and a space-filling line (D =2) are plotted to show the physical bounds to indicate that the temperature clusters have fractal perimeters. (b) Hotspot size distribution in the form of exceedance probability plots at the percolation threshold (in blue) and higher. Choice of axes is log-log to demonstrate the power-law tail behavior (Slope = 2.06). The vertical dashed line is the start of the power-law tail as estimated using algorithms from Clauset et al (2009).

### 3.2 Hotspot size distribution

At first when the thermal threshold increases, the total number of hotspots increase as the biggest connected cluster disintegrates into its constituents (figure 3b). However, after the percolation threshold, any further increase in the threshold causes a net reduction in the total number of hotspots as well as their respective areas (figure 3c). At the percolation threshold, i.e. 70th percentile, in this case, the hotspot size distribution (figure 4b) is found to be consistent with a power-law tail scaling as:

$$P(A \geq a) \propto a^{-(\beta-1)}, \forall a \geq a_{min} \tag{2}$$

Alternative distributions, such as log-normal, exponential and Weibull, were tested as potential candidates; however, they were all rejected (at $p \geq 0.1$). On the other hand, Kolmogorov-Smirnoff statistics suggested that the distributions could not be rejected as a power-law tailed distribution with the exponent $\beta = 2.06$ (at $p \leq 0.1$). This is another salient finding of our analysis. Empirical distributions of land classified as urban[39] and simulated cities modeled with correlated percolation[13] have also found $\beta \sim 2$. For several other systems including: cities;[40] lakes;[36] and islands;[31] the exponent has been reported to be $\sim 2$ as well.

Among reasons for frontal truncation of power-law in real fractal systems is the limitation of resolution. Moreover, in this case, the lower bound ($x_{min}$ at which the power-law tail starts) is about 300 m (figure 4b); which corresponds to the size of an urban block that is the building block of a city. On the other hand, the distribution cannot follow a power-law to arbitrarily large cluster sizes since the area of a cluster can be no bigger than the area of the whole lattice. So the tail of the power-law distribution is truncated, an example of a finite-size effect.[41] As the temperature threshold increases, as the number of hotspots for any given size decreases, the exceedance probability plot shifts to the left (figure 4b). This deviation from the power-law can be modeled as an exponential tempering (equation 3).

$$P(A \geq a) \propto a^{-(\beta-1)} \cdot e^{-c \cdot a}, \forall a \geq a_{min} \tag{3}$$

## 4. SUMMARY

In summary, a framework for characterization of intra-city SUHI is presented using metrics such as area-perimeter Fractal Dimension (D) and slope of hotspot size distribution ($\beta$) at the percolation threshold. Previous studies have shown that the fractal behavior in urban dynamics can be attributed to Diffusion-Limited Aggregation (DLA).[13,42] Our understanding is that the fractal behavior in SUHI is a direct extension of this. As the city grows, urban infrastructures evolve through expansion and densification as parallel processes, involving partial preferential settlement.[18] Such evolution results in an aggregation of heat sources and contributes to the emergence of hotspots.

Moreover, both the fractal dimension as well as scaling exponent estimated here are consistent with that of urban form simulated as a correlated percolation.[13] Such growth patterns are constrained not only by city size but other constraints, including engineering design and socio-economic factors, are manifested as an exponential tempering of the power-law tails. We observe similar tempering emerge above the percolation threshold. Further research on the temporal analysis of intra-urban hotspots focusing on diurnal, seasonal, or decadal variability is also necessary to examine if these spatial patterns are persistent, recurrent and whether there are consistent patterns as cities grow.

Lastly, our analysis here uses Land Surface Temperature as an input. However, a heat-stress vulnerability of urban communities requires the joint consideration of air temperature and humidity.[43] Air temperatures show moderate to good correlations with LST depending upon the land use,[44] but local weather patterns and mixing in the atmospheric boundary layer will likely modify the scaling exponents between cities. As we have demonstrated that a suite of fractal analysis tools lend themselves aptly to the characterization of spatial complexities SUHI, the same can be done for intra-urban heat stress characterization for improved assessment of urban and ecological heat-related impacts.

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