THE IMPACT OF SPATIAL ARRANGEMENTS OF BUILT LAND COVER TYPES ON URBAN WARMING

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ABSTRACT: While the relationship between fractional cover of built features and the urban heat island (UHI) has been well studied, relationships of how spatial configuration (e.g., clustered, dispersed) of these features influence urban warming are not well understood. As buildings and paved materials are defining features of the urban environment it is important to explore the spatial pattern of these features to understand how they influence urban warming effect. The goal of this study is to examine if and how spatial arrangements of anthropogenic features (buildings, paved surfaces) influence land surface temperatures (LST) in an urban environment. This study focuses on Las-Vegas, NV, a desert city that has undergone dramatic urban center expansion and population growth since the 1960s. The data used to classify land cover and extract building consist of Geoeye-1 (formerly Orbview 5) image. The image used was taken on October 12, 2011 and has a spatial resolution of 3m. Classification was carried out using object based image analysis (OBIA). A spatial autocorrelation approach (i.e., local Moran's *I*) that measures the spatial dependence of a point location to its neighboring points and describes how clustered or dispersed points are arranged in space was employed. Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data acquired on July 6, 2005 (daytime) and August 27, 2005 (nighttime) were regressed against spatial patterns of anthropogenic features. Results from this study suggest that clustered spatial arrangements of buildings and paved surfaces elevate surface temperatures more severely.

1. INTRODUCTION

The world population is projected to reach 9.6 billion in 2050 based on the medium-variant projection (UN, 2013). The increasing population will inevitably lead to a more urbanized world, as the majority (more than one half) of the population will reside in cities. Sustainable city design and the ways in which city dwellers live their daily lives, thus, play crucial roles in minimizing required inputs of energy, water, and food, and reducing waste output of heat, air pollution, and water pollution (Kramers et al., 2014). Building sustainable cities is a must to achieve a sustainable world. The Urban Heat Island (UHI) effect is a well-known phenomenon caused by urbanization — a process of altering natural surfaces with manmade features that significantly change the energy balance and affect the urban thermal environment (Hart and Sailor, 2009). The UHI effect not only has impacts on air quality, water consumption, and energy use, but also increase the magnitude and duration of heat waves in cities which often elevate risks of heat related illnesses and deaths (Brazel et al., 2007).

High-spatial resolution imagery not only opens the possibilities to study detailed land cover features and different man-made materials on LST, but also provides the capability to examine the spatial characteristics and arrangement of land cover patches on LST. Landscape metrics, such as patch density, edge density, and landscape shape index, were widely used to examine the impacts of spatial configuration of land cover features on LST (Li et al., 2011; Maimaitiyiming et al., 2014). These studies found that spatial configuration has significant impacts on LST, indicating that spatial configuration can be optimized to mitigate the UHI effect. However, the readily available landscape configuration metrics from FRAGSTATS software used in these studies, especially the metrics at the landscape level which consider all patch types simultaneously, are not well designed to provide direct interpretation and information on how to spatially design and arrange a specific land cover type to achieve effective UHI mitigation. For instance, Li et al. (2011) resulted in positive correlations between LST and edge (patch) density, and a negative relationship between LST and Shannon's Diversity Index (SHDI) at the landscape level. The SHDI measures land cover diversity in landscape. Their results suggested that several greenspace patches provided a stronger UHI mitigation effect than its concentrated form based on their results (Li et al., 2011). For another study, Zhou et al. (2011) reported that increases in edge density of woody and herbaceous vegetation decreases LST, and that increases in shape complexity and variability of buildings and paved surfaces leads to an increase in LST. In addition, configuration metrics often have good correlations with composition metrics (Riitters et al., 1995). Therefore, it is necessary to control for the effects of composition when examining the effects of configuration of land cover features on LST. One effective way to address the above limitations is to use geostatistical techniques. Two spatial autocorrelation indices, i.e., local Moran's *I* and Getis, have been applied to examine the impacts of spatial patterns of green space on temperature (Myint, 2012). Local Moran's *I* was found effective on characterizing dispersed and clustered patterns of land cover features (Fan and Myint, 2014, Baojuan, et. al., 2014). Given the above background, this study aims to answers these questions: (1) Does the spatial pattern of anthropogenic features influence LST? (2) Are the impacts of spatial pattern on LST similar in magnitude among different built features? (3) Do spatial pattern of built features show similar impacts when other land cover fractions are controlled?

2. STUDY AREA AND DATA

Las Vegas, the most populous city in Nevada with 1.9 million people living in its metropolitan area, was chosen. The city is located in a basin on the floor of the Mojave Desert, this subtropical desert city's hottest months fall in between June and September (NOAA 2013).

2.1 High Resolution Satellite Data

The data used in this study include high resolution multispectral satellite imagery for detailed urban land cover classes and daytime and nighttime surface temperature data over Las Vegas. We employed Geoeye-1 high resolution satellite data over Las Vegas. The Geoeye-1 image was taken on October 12, 2011. The image has a spatial resolution of 3m with 4 bands: Blue (0.45 – 0.51 μm), Green (0.51 – 0.58 μm), Red (0.66 - 69 μm), and Near Infrared (0.78 – 0.92 μm). The object-oriented approach that aggregates pixels into discrete image objects (Benz et al, 2004) was employed to identify urban land cover classes (i.e., buildings, trees/shrubs, grass, unmanaged soil, paved surfaces, water). Figure 1 shows a Geoeye-1 and its output over Las Vegas.

(a) (b)

Figure 1. (a) Geoeye-1 image over Las Vegas displaying near infrared (NIR) in red, visible red in green, and visible green in blue; (b) Classified output.

2.2 Land Surface Temperatures

We used Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) images at 90 m spatial resolution to examine daytime and nighttime differences in LST. ASTER summer daytime temperature data was acquired on June 10, 2011 and nighttime temperature data was acquired on October 17, 2011 (Figure 2). The Kinetic (K) temperature data (i.e., ASTER08) was used to convert temperatures into Celsius (JPL 2001).

(a) (b)

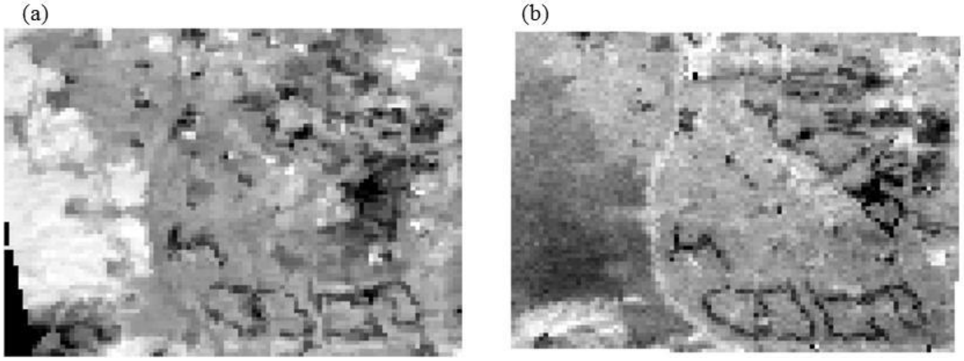

Figure 2. (a) ASTER daytime LST (June 10, 2011); (b) ASTER daytime LST (October 17, 2011).

3. METHODOLOGY

A spatial measure called local Moran's *I* was employed as a local indicator of spatial association (LISA) to characterize spatial configuration (from clustered to dispersed) of urban landscapes at a local scale (Fan and Myint, 2014). It is defined as

$$I_i(d) = \frac{x_i - \bar{x}}{\sum_i (x_i - \bar{x})^2} \sum_j w_{ij}(d)(x_j - \bar{x}) \tag{1}$$

where x_i represents the attribute value (i.e. zero or one in the binary map) at location i and $\bar{x}$ denotes the average attribute values for pixels in the entire image. $\{w_{ij}(d)\}$ is a spatial weight matrix where the diagonal elements are all zero, and the off-diagonal elements are either one or zero, depending on whether the corresponding pixels are neighbors or not. The neighborhood was defined by the distance *d*.

The average local Moran's *I* values were normalized to the range of −1 to 1. Local Moran's *I* values of −1 represent highly dispersed patterns, values of zero indicate random patterns, and values of 1 represent highly clustered patterns. Figure 3 shows hypothetical spatial patterns of a land cover type (e.g., value 1 = paved) and their corresponding local Moran's *I* values. We extracted individual land cover type (i.e., buildings, paved) separately and assigned value one to pixels with a land cover type and zero to other pixels. We then computed local Moran's *I* values for every 90m x 90m area to match with ASTER resolution (90m). The Pearson correlation was employed to evaluate the impacts of the spatial pattern of anthropogenic fractions on LST. To minimize the effect of land cover composition on LST, we further controlled for the land cover composition by grouping similar compositions of land cover types. Because it is almost impossible to obtain even for a few observations with the same amount of fraction for each land cover type, we grouped them based on a 10% fraction range by separating groups at 10% interval: 0–9%, 10–19%, 20–29%, 30–39%, 40–49%, 50–59%, 60–69%, 70–79%, 80–89%, 90–100%.

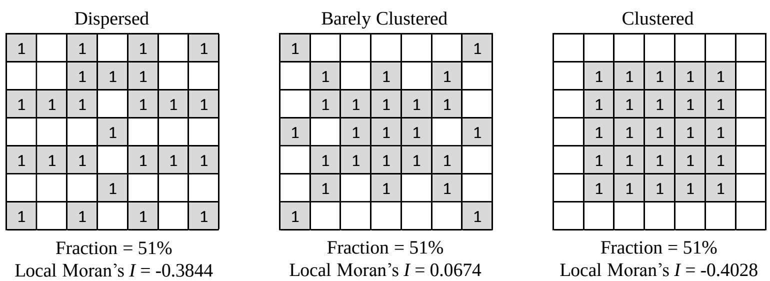

Figure 3. Three hypothetical spatial configurations of a land cover (e.g., paved surface = 1) in a 7x7 grid area and local Moran's *I* values.

4. RESULTS

4.1 Effects of anthropogenic land cover features on LST

Paved surface fractions are positively correlated to daytime temperature (R = 0.44) and nighttime temperature (R = 0.52) implying that the higher the paved surface fractions the higher the surface temperatures. They both showed statistically significant correlations. Even the relation between paved surface and nighttime LST are stronger the slope value with daytime LST was higher meaning that paved surface fractions have greater impact on LST. Building fractions for both daytime (R = 0.25) and nighttime (R = 0.10) showed very little positive correlation to LST. The main explanation is that not every building structure interacts with its local environment the same. Residential homes in these areas, often only one to two stories high, have been found in previous studies to show a positive relationship with surface temperatures (Myint 2013). These houses are usually covered with darker rooftops, which absorb more heat. On top of this, the lower height these structures possess does not provide significant shade to cool the areas they surround (Myint 2013). Commercial buildings, on the other hand, often have the opposite effect on UHI—they can actually cool down their local environments. This is because these large buildings usually have high albedo roofs—meaning light-colored rooftops that reflect sun more efficiently and thus absorb less heat (Myint 2013). During the daytime, commercial structures also provide large amounts of shade to areas directly around them, which reduces the amount of sun hitting surfaces, thus also lowering UHI. Because of these differences in size, material, and location between residential and commercial buildings, their overall relationship to LST is harder to determine and must be observed in greater detail.

4.2 Impact of anthropogenic features' spatial patterns on LST

Local Moran's *I* was used to examine the correlations between spatial patterns of the various land cover features to LST. For impervious structures, such as paved surfaces and buildings, there is a positive correlation between local Moran's *I* of anthropogenic surfaces and LST, meaning as the feature becomes more clustered (closer to 1.0), it increases surfaces temperatures greater. The spatial arrangement of paved surfaces had strong positive correlations to surface temperature; however, nighttime proved to have higher R values, thus showing a greater relationship.

Although spatial configuration of buildings showed a slightly positive correlation with LST, their daytime and nighttime R values were too low to be significant. Since R values for paved surface spatial configuration were greater at nighttime, only these temperatures were grouped (Table 1) to demonstrate if and how spatial configuration of built materials influence surface temperatures. Out of all 25 groups, almost all had statistically significant correlations ($R > 0.30$) between spatial pattern of paved surfaces and LST. 9 groups were found to have medium to strong ($R > 0.45$) spatial configuration to nighttime surface temperature relationships. Hence, we presented the groups that show correlations higher than 0.3. Among them a group with only 20-29% paved fraction ($R = 0.60$) shows a strong paved surface spatial relationships to LST. For this particular group with paved surface fractions of 20-29%, soils were 20-29%, greenery was 10-19%, and buildings consisted of 30-39%. The observations in this group ranged from fairly dispersed (Local Moran's *I* of -0.64), to almost random (Local Moran's *I* of -0.09). The R value (0.6) here was one of the highest recorded, meaning the spatial arrangement of paved surfaces under this land composition has a very strong relationship to LST. As we can see, the less dispersed paved surfaces become under these conditions, the greater the increase in surface temperatures. If paved surfaces are more dispersed between big buildings especially in downtown commercial areas, it increases the likelihood that each section will see shade as some point in the day. However, if they become less scattered, and more clustered together, there is a possibility that a large percentage of the paved surface fraction may never receive shading, and thus will heat up nighttime LST greater because of all the sunlight absorbed during the day. To solidify our conclusions, we would like to take a look at another group with paved surface fractions of 70-79%, soils 0-9%, greenery 10-19%, and buildings 0-9%. This group's observations ranged from barely dispersed (Local Moran's *I* of -0.33) to somewhat clustered (Local Moran's *I* of 0.78). The high R value (0.61) of this group indicates that, once again, the spatial configuration of paved surfaces has a strong relationship with LST when vegetation also has relatively high fractions. As paved surfaces become more clustered when near vegetation, nighttime temperatures increase.

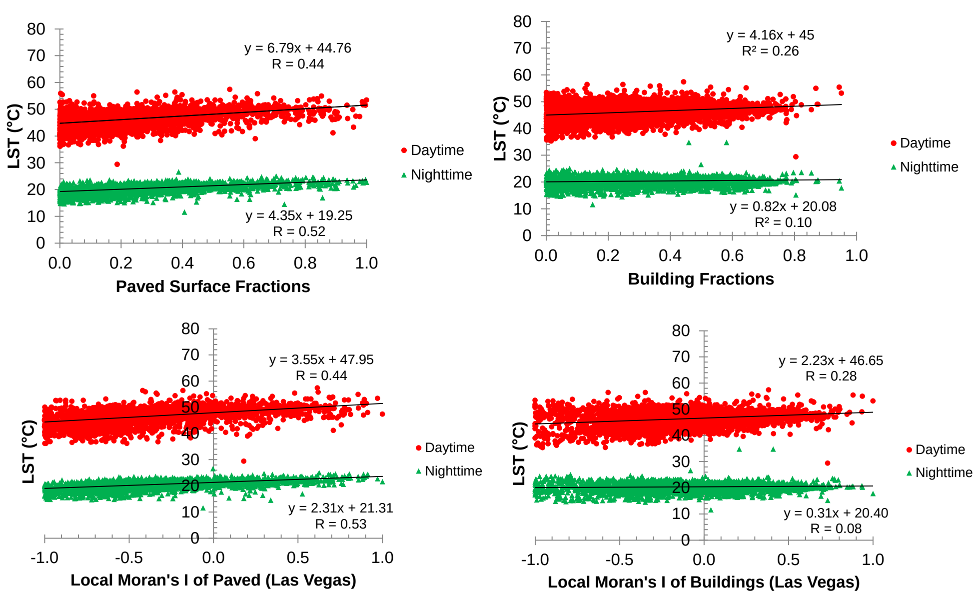

Figure 4. Regression models and scatterplots of buildings and paved surfaces vs. daytime and nighttime LST.

5. DISCUSSION

The results above showed that different built cover features have varying impacts on surface temperatures. When looked at separately, each observed feature had a slightly different daytime and nighttime relationship to LST. Paved surfaces show positive correlations to LST. Paved surfaces were shown to raise temperatures as the feature's percentage increased. However, a significantly stronger relationship was observed at nighttime, meaning paved surfaces are more effective at raising LST during this period. As discussed previously, these impervious surfaces, such as asphalt, are much better at trapping heat during the day. After the sun goes down, these paved surfaces release all of that absorbed heat into the air, causing an unnatural influx in nighttime temperatures.

The spatial configuration of paved surfaces had a stronger positive relationship to LST during nighttime. Even though this land feature also increased daytime temperatures significantly as its spatial pattern became more clustered, the effectiveness of its clustering on LST was much greater at night. Paved surfaces usually include asphalt and other dark colored impervious materials that release trapped heat during nighttime. When these surfaces are clustered together, their powerful warming effects are aggregated. Because spatial arrangements of paved surfaces had a large effect on LST during nighttime, we chose this land feature to observe in groups and controlled for its land composition. The results from this study showed that the clustering effect of paved surfaces is most effective at raising surface temperatures when combined near soil. Previous studies have also found this to be true, and recommend that city managers should target areas with large patches of paved surfaces and soils to better mitigate the UHI (Zheng et al., 2014). These types of areas are usually large parking lots or highways surrounded by open soils. Current city planners can help lower surface temperatures by clustering together vegetation and trees in between the plots of paved surfaces. Our results also showed the spatial pattern of paved surfaces that have a very strong positive relationship to nighttime LST when building fractions were also high.

Table 1. Pearson correlation between local Moran's *I* of paved surfaces and daytime nighttime LST under different controlled land cover compositions (only those groups with r > 0.3), number of samples (n), minimum (Min.) and maximum (Max.) values of local Moran's *I*.

Land cover %				Moran's *I*					
Paved	Soil	Vege	Bld.	Min.	Max.	r	r^2	Slope	n
10-19	0-9	20-29	50-59	-0.79	-0.28	0.45	0.20	5.73	136
10-19	10-19	20-29	40-49	-0.75	-0.34	0.37	0.14	5.34	58
10-19	0-9	40-49	30-39	-0.77	-0.23	0.30	0.09	3.29	90
20-29	10-19	0-9	50-59	-0.69	-0.29	0.55	0.30	5.58	18
20-29	0-9	10-19	40-49	-0.58	-0.24	0.39	0.15	5.64	30
20-29	10-19	10-19	40-49	-0.69	-0.08	0.33	0.11	2.51	40
20-29	0-9	10-19	50-59	-0.65	-0.15	0.37	0.14	4.26	166
20-29	10-19	10-19	50-59	-0.69	-0.21	0.31	0.10	2.90	44
20-29	0-9	10-19	60-69	-0.65	-0.22	0.53	0.28	5.99	40
20-29	20-29	10-19	30-39	-0.64	-0.09	0.60	0.36	4.85	21
20-29	0-9	20-29	40-49	-0.65	-0.05	0.36	0.13	4.03	199
20-29	10-19	20-29	40-49	-0.60	-0.34	0.45	0.20	6.52	17
20-29	0-9	20-29	50-59	-0.65	-0.09	0.40	0.16	4.22	64
20-29	10-19	30-39	20-29	-0.68	-0.19	0.39	0.15	4.17	20
20-29	0-9	30-39	30-39	-0.58	-0.25	0.35	0.12	4.04	131
30-39	10-19	20-29	20-29	-0.50	0.20	0.49	0.24	4.12	24
30-39	0-9	30-39	30-39	-0.51	0.07	0.41	0.17	3.15	42
40-49	10-19	10-19	30-39	-0.39	0.42	0.39	0.15	2.19	82
40-49	0-9	10-19	40-49	-0.28	0.22	0.30	0.09	2.45	27
40-49	20-29	20-29	10-19	-0.36	0.23	0.40	0.16	2.73	61
50-59	0-9	10-19	30-39	-0.12	0.49	0.35	0.12	2.46	55
60-69	0-9	20-29	10-19	0.11	0.51	0.50	0.25	7.65	22
70-79	0-9	0-9	10-19	0.34	0.76	0.47	0.22	7.93	22
70-79	0-9	10-19	0-9	0.33	0.78	0.61	0.37	4.95	15
80-89	0-9	0-9	0-9	0.49	0.91	0.36	0.13	4.32	20

Clustered paved surfaces may increase nighttime surface temperatures more effectively when building percentages are also high because these paved areas are less likely to receive shading during the day from those commercial buildings when they're bunched together. If these sidewalks, asphalt roads, and other paved materials were broken up by large patches of trees or grass, which would provide shade and also have been shown to effectively lower LST through evapotranspiration, the UHI would be efficiently lessened.

Buildings were shown to have a weak positive relationship to LST during daytime and nighttime, although, the former is stronger. This can be explained by looking at the varying types of buildings observed. Many commercial buildings showcase solar insulation qualities, and actually reduce temperatures around them, meaning they are UHI friendly (Myint 2013). Residential buildings, on the other hand, increase daytime surface temperatures due to their dark colored roofs that absorb more heat (Myint 2013). The negative effects of these residential homes help to explain why buildings have a stronger positive relationship to LST during the daytime. The spatial patterns of buildings showed a weak relationship to daytime LST, and an even weaker relationship to nighttime surface temperatures. The closer these buildings are located next to one another, the less spread-out shade they will be able to provide to paved surfaces throughout the day.

6. CONCLUSION

We found that impervious materials, such as roads, parking lots, and driveways had a strong positive relationship to surface temperatures, meaning they *raise* LST as their percentages increase. Generally, buildings were found to have a slightly positive relationship to LST; however, this data needs to be observed in greater depth, due to commercial buildings' ability to decrease the UHI (Myint 2013). The spatial configuration of paved surfaces had the highest impact on surface temperatures at night; this was the chosen group to control for land composition as a nighttime indicator. It was found that, when paved surface fractions were high (>50%), and soil fractions were also significant (>20%), the spatial configuration of paved surfaces showed a very strong relationship to nighttime LST. Using these results, along with those found from previous studies, city managers should target these areas and devise a plan that either disperses the paved surfaces (i.e. by adding buildings between them), or introduces greenery that helps mitigate their aggregated warming effects (Zheng et al., 2014). When clustered together, and located near a large percentage of buildings, paved surfaces were much more effective at raising nighttime LST. In order to combat this effect, future city planners in Las Vegas and other arid cities should disperse buildings as much as possible in between paved asphalt, sidewalks, and other paved materials. This way, shade provided by commercial buildings has a greater potential to cool down surface temperatures, as it is spread out more between the local environments.

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