UNDERSTANDING THE RELATIONSHIP BETWEEN URBAN LAND SURFACE TEMPERATURE AND LANDSCAPE HETEROGENEITY AND SOCIAL STRUCTURE

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Urban heat island refers to the phenomenon that ambient air and surface temperatures in urban areas are several degrees higher than surrounding rural areas (Voogt and Oke 2003). Higher temperatures not only impact the comfort of urban dwellers, but also increase energy use, ozone production (Akbari et al. 1996, 2001 ; Taha 1997 and Stone 2005) and contribute to heat wave disasters, which have been reported as the predominant cause of death resulting from natural hazards in post industrial societies worldwide (Poumadere et al. 2005). Understanding the spatial pattern of land surface temperature (LST) at neighborhood scale is very important for urban planning, heat mitigation efforts and air pollution studies.

This study investigates the effects of landscape heterogeneity and socioeconomic factors on urban LST. The objectives are two-fold: 1) to examine the quantitative relationship between urban LST and variables of landscape heterogeneity and social structure; and 2) to explore whether a combination of variables of landscape heterogeneity and social structure can better understand the pattern of urban LST. We focused on the Gwynns Falls watershed, which is approximately 171.5 km^2, lies in Baltimore City and Baltimore County, Maryland, and drains into the Chesapeake Bay. A Census-based unit, block group, was used as the unit of analysis in this research.

Land surface temperature data were first derived from the thermal infrared (TIR) band (10.44 – 12.42um) of a Landsat 7 Enhanced Thematic Mapper Plus (ETM+) image collected on July 28, 1999, with a resolution of 60 m. The mean of LST was then summarized by block group. Landscape heterogeneity was measured by two different datasets: a high-resolution land cover dataset and normalized difference vegetation index

(NDVI). A set of social variables including ethnicity, income, and education was used to measure the social structure. The percentages of different land cover types for each block group were obtained by using a high resolution land cover dataset for the Gwynns Falls watershed that was derived from the aerial color-infrared aerial imagery collected in 1999, with pixel size of 0.6m (Zhou and Troy 2008). Six land cover classes were included in the land cover dataset including coarse textured vegetation (trees and shrubs), fine textured vegetation (grass and herbs), pavement, bare soil, building, and water (Cadenasso et al. 2007). Due to correlation among the six land cover classes, only percent of building and coarse vegetation were selected as independent variables in the regression analysis. NDVI is a vegetation index that has been frequently used as an indicator of land surface characteristics in UHI studies (e.g. Weng et al. 2004). NDVI data were derived from the same aerial imagery as used for the land cover classification. The mean of NDVI for each block group was obtained by summarizing the NDVI data by block group. Social variables used in this study were median household income, percent of people receiving less than 9 years of education and percent of White people. All the social variables were from Census 2000 and reported at the Census block group level.

Our results reveal that the combination of building and coarse vegetation explained 70.8% of the variation in LST (Model 1, Table 1). LST increases with the increase of percentage of building and decrease of vegetation in a block group. NDVI alone explained about 69% of the variance (Model 2, Table 1). LST decreases with the increase of NDVI. The three social variables collectively explain about 50% of the LST variance (Model 3, Table 1). The combination of socail variables with those of landscape heterogeneity slightly increase the power of the models (Model 4 and 5), but not significantly. This might due to the substaintial overlaps among the LST variations explained by land cover variables and social factors (Figure 1).

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Table 1 The five models and their independent variables; the dependent variable for all of the models was LST.

Models	Independent Variables	Adjusted R^2
(1)	Building% + CoarseVeg%	.708
(2)	NDVI	.690
(3)	Less9yrEdu % + Income + White %	.531
(4): (1)+(3)	Building% + CoarseVeg% + Less9yrEdu % + Income + White %	.743
(5): (2)+(3)	NDVI + Less9yrEdu % + Income + White %	.717

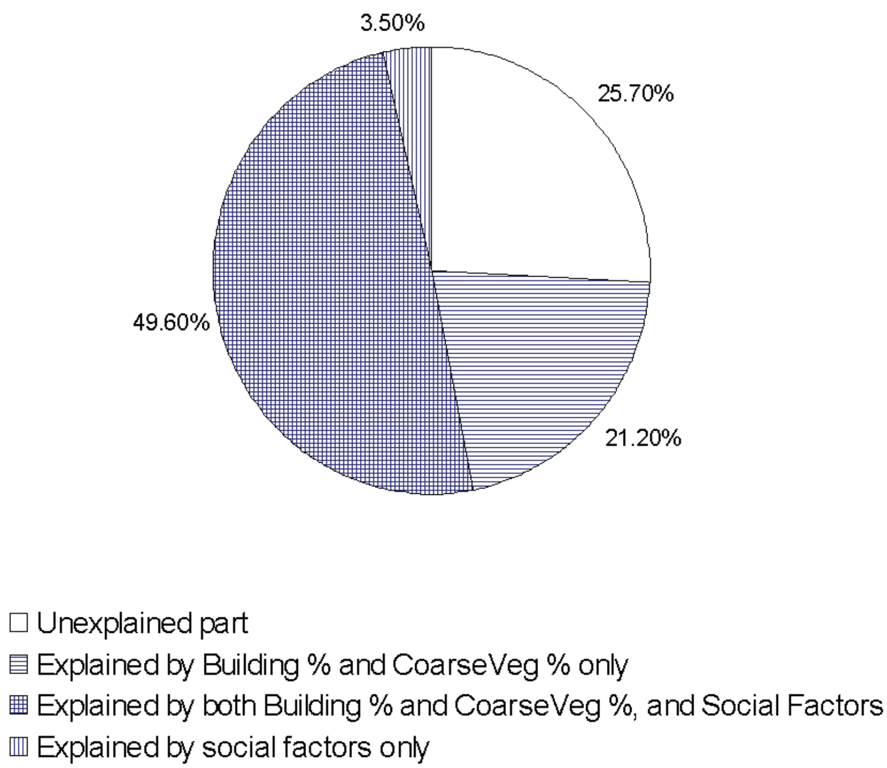

Figure 1. Proportions of variation in LST explained by land cover variables and social factors