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RESEARCH ARTICLE

People, landscape, and urban heat island: dynamics among neighborhood social conditions, land cover and surface temperatures

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Abstract
Context Urban heat island studies have found that land cover, neighborhood social conditions and temperatures are correlated. This received great academic attention because of potential ecological, social and health impacts. However, the processes and causalities behind such correlations remain unclear, which impede designing effective heat mitigation approaches.
Objectives Our study aims to answer two questions: (1) Do social conditions influence temperature independent of land cover? (2) Is land cover more closely associated with temperature than neighborhood social conditions or vice versa?
Methods The analysis is for the year 2000 and the Gwynns Falls watershed in Baltimore, Maryland. Census data for 297 block groups and remote sensed data for land cover and surface temperature were used. To answer question 1, we used structural equation modeling to build and compare model fitness. We conducted partial correlation and regression analysis to answer question 2.
Results Land cover (building and trees) leads both social conditions (race and income) and temperature to vary across space. When holding land cover constant, social conditions significantly contribute to temperature variation.
Conclusions This study extends understanding beyond simple correlation and determined that land cover influences the spatial variation in neighborhood social conditions and temperature.

Keywords Urban heat island · Neighborhood social condition · Land cover · Land surface temperature · Structural equation modeling · Baltimore

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Introduction

Higher temperatures in cities, referred to as urban heat island (UHI), increase energy and water use (Oke 1982; Arnfield 2003), lead to alterations to biotic communities, and pose an exacerbated yet uneven threat to human health (Basu and Samet 2002; Klinenberg 2002; Harlan et al. 2006). Land transformation during the urbanization process—converting lands from vegetation and bare soil to buildings, roads and impervious surfaces—is the main cause of the UHI (Oke 1995). Other causes include urban structures such as streets and buildings that change radiative fluxes and anthropogenic heat release such as that associated with fossil fuel combustion to power vehicles and industrial processes and the use of air conditioners (Arnfield 2003). Urban heat island modeling studies have found that vegetation cover and impervious surfaces are the most important elements in the urban landscape for explaining variation in heat distribution (Oke 2006; Gartland 2011).

The spatial distribution of heat in the urban area is not homogenous. In a previous study we found land surface temperature (LST) to vary by more than 16 °C across the City of Baltimore (Huang et al. 2011). The heterogeneity in LST distribution is certainly influenced by the physical elements of the system. But the variation in social conditions (i.e. income, race, education) across the system influences the differential exposure to excess heat experienced by urban residents. The social conditions of a neighborhood are receiving increased attention in UHI studies because of the potential for these social conditions to influence the health consequence of excess heat exposure (Wilhelmi and Hayden 2010; Romero-Lankao et al. 2012). Social conditions have been found to be related to LST. Neighborhoods with characteristics such as more ethnic minority residents, residents with lower income and education, and an aging population often experience higher LST than other neighborhoods (Klinenberg 2002; Hope et al. 2003; Buyantuyev and Wu 2010; Huang et al. 2011). Furthermore, social conditions may determine people's ability to mitigate and adapt to heat, such as the use of air conditioners (Klinenberg 2002; Uejio et al. 2010).

The understanding that neighborhood social conditions increase heat risk inspired two divergent but relevant research approaches to incorporating social conditions into UHI studies. One approach estimates neighborhood heat vulnerability by constructing a neighborhood heat risk/vulnerability index based on social conditions, land cover types and LST. This index does not examine the relationship among these variables but rather uses the variables to calculate the index. The spatial variations of the neighborhood heat risk/vulnerability index can then be mapped to illustrate which neighborhoods are the most vulnerable to excess heat (Reid et al. 2009; Johnson et al. 2012). The second approach investigates the relationship between neighborhood social conditions and LST. By examining this relationship, studies found that demographic and socioeconomic factors, such as race, population density, household income and crime levels, are significantly correlated with the spatial variation in LST (Jenerette et al. 2007; Buyantuyev and Wu 2010; Huang et al. 2011). Correlation between land cover types and LST can likely be explained by physical processes of radiative fluxes and surface material characteristics (Forman 2014). In contrast, the correlation found between neighborhood social conditions and LST are much more difficult to explain. The correlation between LST and social conditions may simply be a manifestation of the impact of land cover on LST as neighborhood land cover types may be correlated with social conditions. For example, studies in Phoenix, AZ and Baltimore, MD found that higher vegetation cover was typically associated with neighborhoods characterized by a greater proportion of White residents and higher average household incomes (Harlan et al. 2008; Huang et al. 2011; Jenerette et al. 2011; Schwarz et al. 2015). Alternatively, social conditions may impact LST independent of land cover by some, as of yet, undetermined mechanism.

We know of no studies, other than Jenerette et al. (2007) that have investigated how social conditions and land cover independently contribute to variation in LST. Jenerette et al. (2007) used path analysis to examine the influence of social conditions on LST and they concluded that this influence was primarily indirect and mediated through vegetation. However, path analysis is not designed to deduce causal relationships from correlations but rather to quantitatively assess relationships that are known or assumed, and to separate direct from indirect effects (Byrne 2013). For example, Jenerette et al. (2007) assumed that vegetation coverage was the intermediate variable between social conditions and LST. This means that the social conditions of a neighborhood determine the amount vegetation cover in that neighborhood, which, in turn, influences LST. Using path analysis, Jenerette et al. (2007) quantified the impact of the neighborhood social conditions directly on LST relative to the indirect impact of social conditions on LST through influencing vegetation cover. However, path analysis does not test whether this assumption, that social conditions influence vegetation cover, holds in reality. Neither does it compare its fitness with other alternative hypotheses such as land cover determining the social conditions of the neighborhood, for example.

To fill this gap, we developed four hypotheses to explain the relationship among social conditions, land cover, and LST variation. We examined these hypotheses through structural equation modeling, partial correlation, and regression modeling. We aim to answer two questions: (1) Do neighborhood social conditions influence the spatial variation of LST independent of land cover? And (2) Is land cover more closely associated with temperature than neighborhood social conditions or vice versa? This second question intends to sort out whether the land cover of a neighborhood causes residents with certain social characteristics to live there or the other way around meaning that the social characteristics of the residents determine the land cover in the neighborhood. We selected percent cover of buildings and trees to describe land cover types because these land cover types most significantly affect LST (Zhou et al. 2011). We used percent of the residents identified as White and median household income to describe neighborhood social conditions because these variables are most frequently used in both research approaches incorporating social conditions into UHI studies that we briefly summarized (Jenerette et al. 2007; Harlan et al. 2008). Race and income of a neighborhood are frequently recognized as factors influencing residents' vulnerability to excess heat as well as correlated with land cover and surface temperature. Our goal is to move beyond correlation in understanding the relationship among neighborhood social conditions, land cover and LST.

Temperature variation is primarily influenced by radiation and air flow. Social factors (such as race and income) play a very minor role (if any) in the physical process of temperature variation in urban areas. Our motivation to articulate the relationship among neighborhood land cover, social conditions and LST is not to understand why temperature is higher in some neighborhoods than others through combining social conditions with land cover variables, but rather to further dismantle the correlation among them to explore what role land cover may play in the correlation between LST and the social conditions influencing residents' vulnerability to excess heat. Therefore, instead of choosing the social factors that may influence LST such as energy use, we selected race and income, which are widely recognized as essential factors in estimating residents' vulnerability.

We want to clarify that the words "influence" and "impact" in the following text did not indicate social conditions can directly change the thermodynamics and generate spatial variations of temperatures. Instead, these words were used from a statistical perspective in the context of examining the correlation among neighborhood social conditions, land cover and LST. Our efforts will contribute to understand the relationship among variations of residents' exposure to excess heat (represented as LST), social vulnerability (represented as race and income) and land cover.

Methods

Study area

We focused on the Gwynns Falls (GF) watershed, a study site of the Baltimore Ecosystem Study, a National Science Foundation funded long-term ecological research program. The GF watershed lies in Baltimore City and Baltimore County, Maryland, and is approximately 171.5 km^2. The watershed traverses an urban–suburban–rural gradient from the urban core of Baltimore City, through older inner ring suburbs to rapidly suburbanizing areas in the middle reaches and a rural/suburban fringe in the upper section. Land cover in the GF watershed varies from highly impervious in the lower sections to a broad mix of uses in the middle and upper sections. The socioeconomic characteristics of watershed residents vary greatly. For example, according to Census 2000, the average median household income ranges from USD 25,217 in the lower sub-watersheds to USD 52,378 in the upper sections (Geolytics 2000). Proportion of White residents in block group varies from 0 to 99.5 % (Geolytics 2000). Variations of land cover and neighborhood social conditions make the GF watershed an ideal site to address our research questions.

Data and analyses

We used block group, a census-based unit, as the unit of analysis in this study. Block groups that are not completely contained within the watershed were retained if they are larger than 50 km^2 and more than 50 % of their land area is in the watershed. One census block, located completely within the watershed, was excluded from the analysis because census data was missing. Consequently, we included 297 block groups in the analysis. We used this block group boundary layer as the common boundary for all geospatial operations.

The mean LST by block group was used as an indicator of neighborhood temperature (Fig. 1a). We obtained the LST data from the thermal infrared (TIR) band (10.44–12.42 μm) of a Landsat 7 Enhanced Thematic Mapper Plus (ETM+) image acquired at approximately 10:30 am on July 28, 1999. Though this is a single snapshot and does not represent temperature variation throughout the year, the remote sensed data does cover a large area and allows us to test relationships between the spatial variation in LST and other variables. The LST of all pixels contained within a block group were averaged to provide the mean LST by block group. The spatial resolution of the TIR band is 60 m. The image was rectified to a common Universal Transverse Mercator coordinate system based on the 0.6 m orthorectified emerge color-infrared aerial imagery collected in 1999 (Zhou and Troy 2008), and was resampled using the nearest neighbor algorithm with a pixel size of 60 m for the thermal band. The resultant total root mean square error was found to be less than 0.3 pixels. Further details on calculating LST are documented in Huang et al. (2011).

The percent of different land cover types for each block group was calculated from a 0.6 m land cover classification map (Fig. 1b, c). This classification map was created using an object-based classification approach (Zhou and Troy 2008) on color-infrared aerial imagery collected in 1999. Five land cover classes were included: woody vegetation (trees and shrubs), herbaceous vegetation (grass and herbs), pavement, bare soil and building (Cadenasso et al.

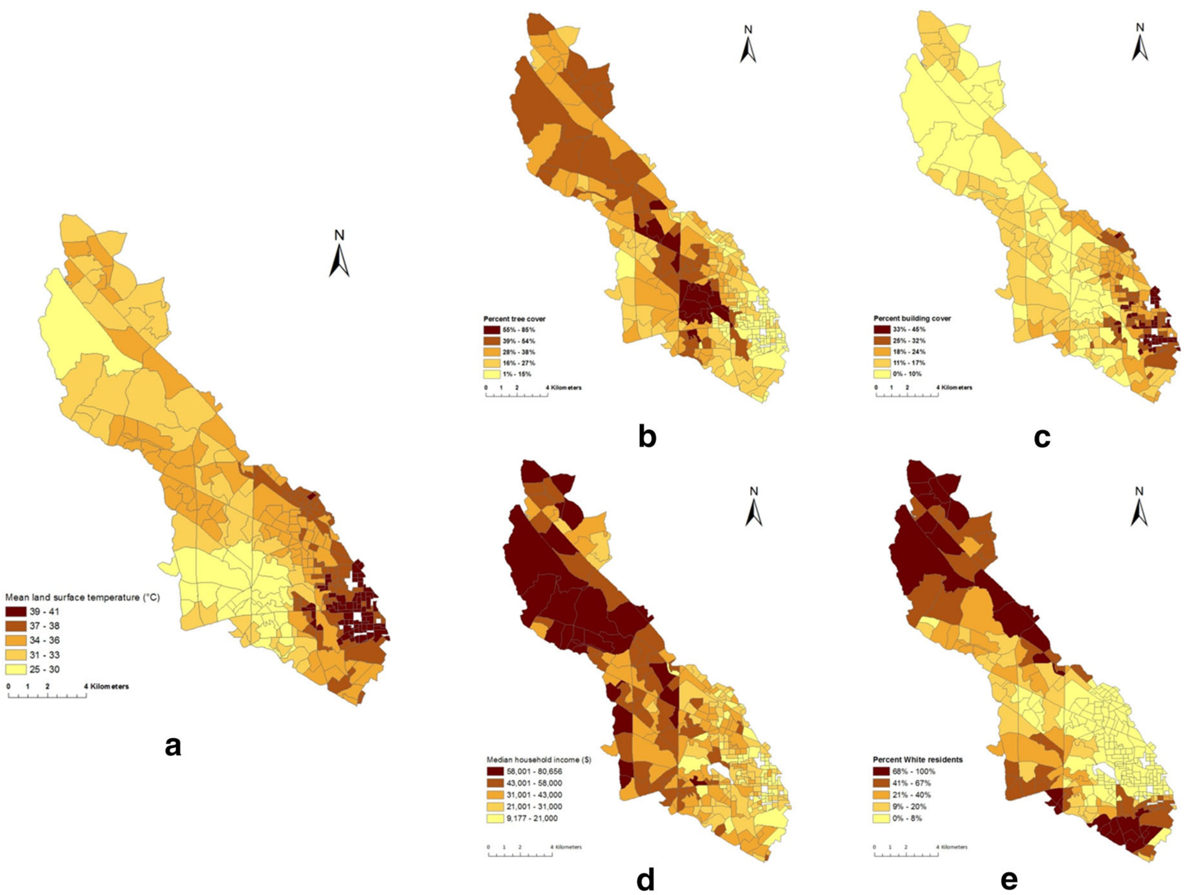

Fig. 1 Spatial variations of neighborhood **a** land surface temperature, **b** trees, **c** building, **d** income and **e** percent White residents

2007). The overall accuracy of the classification was 92.3 %, with producer's accuracies ranging from 88.3 to 100 %, and user's accuracies in the range of 83.6–97.7 %. Further details about the classification methods and results are documented in Zhou and Troy (2008). Neighborhood social conditions are reported at the census block group level (Fig. 1d, e) and are from the 2000 US Census (Geolytics 2000).

We developed four hypotheses based on the two research questions (Fig. 2). Question one asks whether neighborhood social conditions influence LST independent of land cover. In other words, this question asks whether the blue arrow from social conditions to LST in Fig. 2 exists. The second question seeks to identify whether social conditions or land cover is more closely associated with temperature variation across space than the other. In other words, which direction would the red arrow between land cover pattern and social conditions point (Fig. 2). Four hypotheses are proposed:

H1 Land cover influence LST directly as well as through modifying neighborhood social conditions. Social conditions influence LST independent of land cover (LC).

H2 Neighborhood social conditions influence the spatial variation in LST directly as well as through modifying land cover patterns.

H3 Land cover influence spatial patterns of LST and neighborhood social conditions. Social conditions do not influence LST independent of LC.

H4 Neighborhood social conditions influence the spatial variation of LST only through modifying land cover patterns and do not influence LST independent of LC.

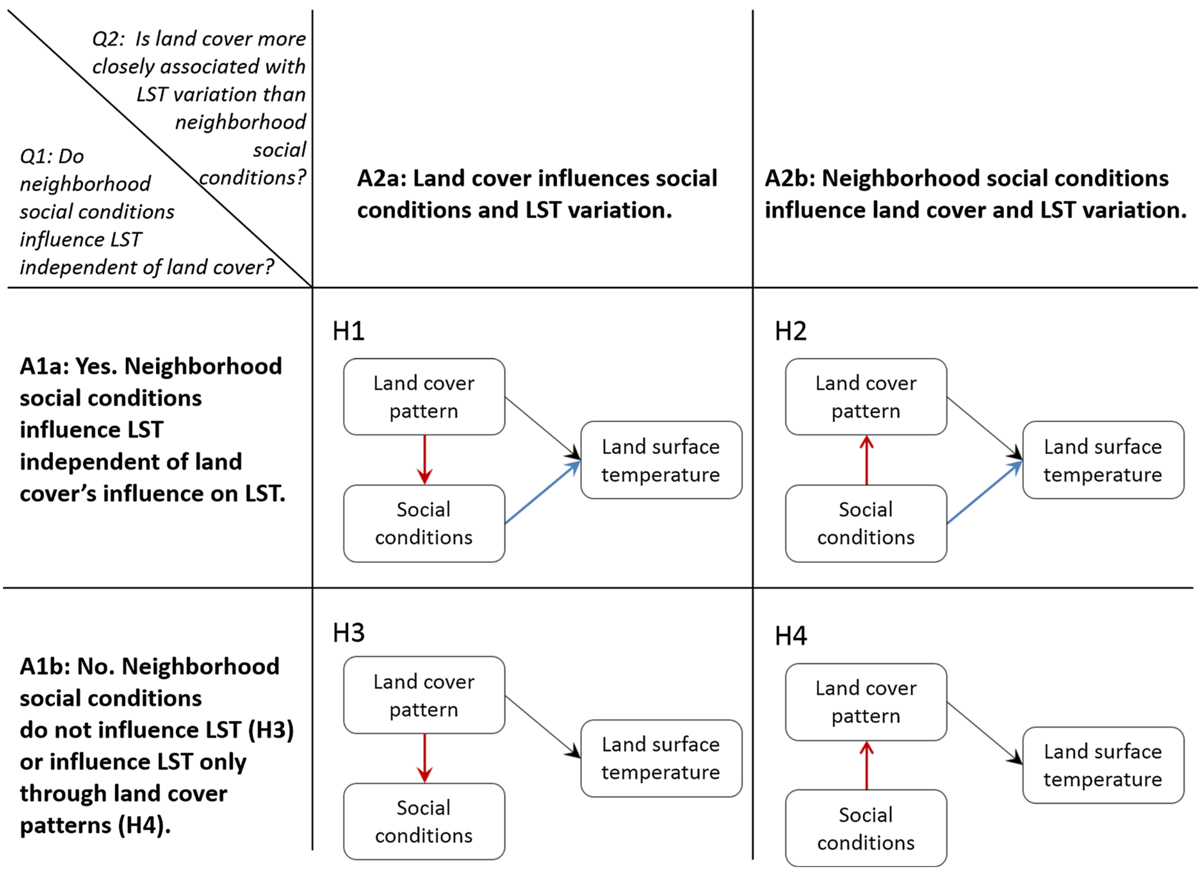

Fig. 2 Possible relationships between neighborhood social factors, land cover and temperature. Questions 1 and 2 generated four hypotheses (H1–H4). Each hypothesis represents a different assumption

We used structural equation modeling to test H1 and H2. Structural equation modeling is an extension of general linear modeling and it enables researchers to test causal relations among multiple variables (Kline 2010). While these statistics cannot build a theory to explain why one factor may cause another, they can determine that one factor is more likely to cause another rather than the other way around. Causal relationships are hypothesized and the statistics then test these hypotheses to determine whether they are consistent with the collected data (Lei and Wu 2007). In the Analysis of moment structures (AMOS) software, we first built hypothesized models according to H1 (LC model) and H2 (Social model), respectively (Fig. 3). We then ran both models using our data and calculated four model fitness indices to determine how consistently each model fit the collected data. The model fitness indices are Akaike information criterion (AIC), normed fit index (NFI), p of close fit (PCLOSE), and the Hoelter index. We used four indices because a good fit indicated by one index may not be echoed by another and using only one index may be criticized as "cherry-picking" the index that best supports key conclusions (Hooper et al. 2008).

To test H3, we conducted a partial correlation to examine the impact of social conditions on LST while controlling for the LC variables. If LST is not correlated with social conditions when LC variables are controlled, then we accept H3 that LC variables influence LST and neighborhood social conditions, and conclude that social conditions do not influence LST independent of LC variables. To test H4, we conducted a regression analysis with LST as the dependent variable and LC and social conditions as independent variables. If social conditions are not significant in this regression, then we accept H4 that neighborhood social conditions only influence LST through modifying land cover patterns, and conclude that social conditions do not influence LST independent of LC. We used two different approaches to test H3 and H4. Because H3 has three "dependent" variables (LST, income and White residents %) and two "independent" variable (building % and tree %), we used partial correlation to examine whether the correlations measured from the Pearson correlation between social variables and LST were spurious. H4, on the other hand, has one "dependent" variable (LST) and four "independent" variables (building %, tree %, income, and White residents %). We used multivariate regression to determine whether social variables contribute to explaining the spatial variation in LST. We did not consider spatial autocorrelation in the models. According to previous studies (e.g., Li et al. 2012), while the magnitudes of regression coefficients based on ordinal least square (OLS) regression models may differ from those based on spatial auto regression models that account for spatial autocorrelation, their directions do not change. These results indicated that if the research focused on the directions and relative importance of predictors, the OLS models work fine by not accounting for spatial autocorrelation.

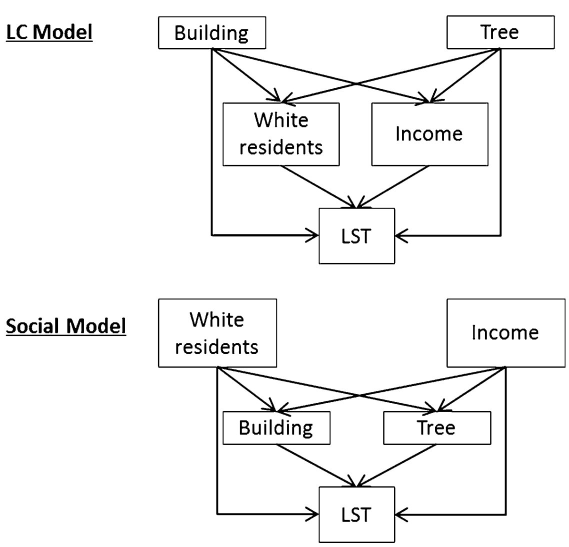

Fig. 3 Conceptual models contrasting driving factors and intermediate factors influencing LST

Results

The four indices used to evaluate model fit do so differently. The AIC index is a comparative measure of fit such that the best model fit is identified by

Table 1 Comparing four model fitness indices

	LC model	Social model
AIC	34	239
NFI (>0.95)	0.993	0.736
PCLOSE (>0.05)	0.059	<0.001
Hoelter index (>200 or 75)	194	6

comparing the index value for each model and the smaller the value the better the fit. In contrast, the other three fit indices indicate fitness of a model by comparing values with a given threshold. Results of the four fit indices all showed a better fit for the LC model than the Social model (Fig. 3; Table 1). The LC model had a much smaller AIC value than the Social model (34 vs. 239), indicating a better fit for the LC model. Results for both NFI and PCLOSE indicated that the LC model had a good fit and the Social model had a very poor fit. A NFI value above 0.95 indicates a good fit, between 0.90 and 0.95 a marginal fit and below 0.90 a very poor fit (Bentler and Bonett 1980). According to NFI values, the LC model had a good fit (NFI = 0.99) whereas the Social model had a very poor fit (NFI = 0.74) (Bentler and Bonett 1980). The cut-off value for PCLOSE was 0.05, and models with a p value above 0.05 are considered a "close" fit (Byrne 2013). The LC model passed the 0.05 cut-off value ($p = 0.06$), but the Social model did not ($p < 0.01$) (Byrne 2013). The Hoelter index has a threshold of 200 meaning that values over 200 indicate a good fit and values less than 75 indicate very poor fit (Byrne 2013). The Hoelter index for the LC model was close but failed to pass the 200 threshold for a good fit with a value 194. The Social model had a value of 6, which indicated a poor fit (Byrne 2013). In summary, the LC model was found to have a better fit for our dataset than the Social model. These results indicate that tree and building cover are more likely to influence the spatial variation in LST directly as well as indirectly through influencing race and income rather than the other way around.

Partial correlation results indicated that both income and race were correlated with LST at a 99 % significance level when tree and building coverage were controlled (Table 2). This means that the correlation between LST and social conditions (income and race) was not entirely due to their relationship with tree and building coverage. Therefore, we rejected H3 that the correlation between social conditions and LST was spurious.

Our regression results showed that LC variables (i.e. percent building and percent tree coverage) and median household income were significant at a 99 % confidence level, and p-value for percent of White residents was 0.07 (Table 3). This means that when controlling for the effects of LC variables, income still significantly (at 0.01 level) contributed to explaining LST variation while the significance of percent of White residents became marginal. Therefore, we rejected H4 that social conditions contribute to LST only through LC variables.

Discussion

Neighborhood land cover impacts the spatial variation of LST directly as well as indirectly through influencing the neighborhood's social composition (i.e. income and race). This understanding provides very important insights on management initiatives aimed at reducing temperature in neighborhoods vulnerable to excess heat. Wolch et al. (2014) argued that neighborhood greening efforts may increase housing costs and property value, which can ultimately lead to displacement of the very residents that the greening efforts aimed to benefit. Our results provide support for Wolch et al. (2014) argument because we found that the land cover of a neighborhood influences its social composition. Despite supporting Wolch et al. (2014) argument, we are not discouraging greening efforts; instead, we argue that more attention should be paid to neighborhood social composition to make sure the greening efforts benefit the targeted residents.

Our results have important implications for environmental justice concerns. Previous studies established correlations between neighborhood social

Table 2 Partial correlation results

	% Building	% Tree	% White residents	Income
LST	+	–	–	–
LST, control % building and % tree	NA	NA	–	–
LST, control % White residents and income	+	–	NA	NA

All directional signs (+ and –) are significant with p-values less than 0.001

Table 3 Results for regression analysis

Dependent variable: LST	Standardized coefficients	Sign.
% Building	0.46	<0.01
% Tree	−0.34	<0.01
% White residents	−0.06	0.07
Income	−0.13	<0.01
Adj-R^2 = 0.724	–	–

conditions and land cover (Harlan et al. 2008; Huang et al. 2011; Jenerette et al. 2011; Schwarz et al. 2015). Here we demonstrate that percent cover of trees and buildings determines race and income of residents. Landscapes experiencing high LST have fewer trees and more buildings and are the neighborhoods characterized by low household income and dominated by residents identified as ethnic minority. Heat, an environmental burden in the summer, is therefore unevenly distributed among segments of the population. Tracking the change of neighborhood land cover patterns and associated change in social conditions over time will enhance our understanding of how, and to what extent, the land cover in a neighborhood influences the social composition of the residents.

Our results indicated that race and income of residents of a neighborhood do have a direct impact on LST independent from land cover. The hypothesis that both LST and social conditions are impacted by land cover and therefore present a spurious correlation (H3) does not hold. The hypothesis (H4) that social conditions influence LST only through changing land cover was also rejected. Rejecting H3 and H4 confirmed that a direct link between social conditions and LST exists.

It is worth noting that variations in residents' income or race of residents in a neighborhood can change the neighborhood temperature only through modifying physical variables, such as surface albedo, wind flows, etc. Existing studies provide little clue on what processes may lead to such effects of social conditions on LST but we suggest several possibilities. First, landscape configuration has an impact on LST (Zhou et al. 2011). Holding composition of the different elements that make up land cover (e.g. buildings and trees) constant, LST can be significantly increased or decreased by the different spatial arrangements of these elements. Neighborhood social characteristics may be associated with certain landscape configurations and therefore have an impact on LST variation across space. Second, neighborhood social characteristics may be associated with certain house/yard features that impact LST but are not captured by LC variables frequently used in UHI studies. Examples include a swimming pool, a water fountain, or green/white roofs. Finally, social characteristics may be associated with certain household decisions such as the use of air conditioners or lawn irrigation practices, which may also influence spatial variation in LST (Polsky et al. 2014). Future studies focusing specifically on how social conditions link to possible household decisions or landscape patterns that may impact neighborhood LST would enhance our understanding of the relationship between neighborhood social conditions and LST and therefore inform potentially more effective heat intervention and mitigation approaches.

Conclusions

We examined the relationships between neighborhood social conditions, land cover and temperatures in Baltimore, MD. We found that neighborhood social conditions, specifically race and income, impact the spatial variation of LST independently from land cover. Furthermore, we found that land cover (i.e. percent coverage of trees and buildings) is the driving force, leading both neighborhood social conditions and LST to vary across space. These findings suggest future research directions on how social conditions influence LST as well as why and how land cover influences neighborhood social conditions.

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References

Arnfield AJ (2003) Two decades of urban climate research: a review of turbulence, exchanges of energy and water, and the urban heat island. Int J Climatol 23:1–26

Basu R, Samet JM (2002) Relation between elevated ambient temperature and mortality: a review of the epidemiologic evidence. Epidemiol Rev 24(2):190–202

Bentler PM, Bonett DG (1980) Significance tests and goodness-of-fit in the analysis of covariance structures. Psychol Bull 88:588–600

Buyantuyev A, Wu J (2010) Urban heat islands and landscape heterogeneity: linking spatiotemporal variations in surface temperatures to land-cover and socioeconomic patterns. Landscape Ecol 25(1):17–33

Byrne BM (2013) Structural equation modeling with AMOS, basic concepts, applications, and programming. Routledge, Abingdon

Cadenasso ML, Pickett STA, Schwarz K (2007) Spatial heterogeneity in urban ecosystems: reconceptualizing land cover and a framework for classification. Front Ecol Environ 5:80–88

Forman RTT (2014) Urban ecology: science of cities. Cambridge University Press, Cambridge

Gartland L (2011) Heat islands: understanding and mitigating heat in urban areas. Earthscan, Washington DC

Geolytics (2000) Census 2000 Long Form dataset. Geolytics Incorporated, East Brunswick

Harlan SL, Brazel AJ, Jenerette GD, Jones NS, Larsen L, Prashad L, Stefanov WL (2008) In the shade of affluence: the inequitable distribution of the urban heat island. Res Soc Probl Public Policy 15:173–202

Harlan SL, Brazel AJ, Prashad L, Stefanov WL, Larsen L (2006) Neighborhood microclimates and vulnerability to heat stress. Soc Sci Med 63(11):2847–2863

Hooper D, Coughlan J, Mullen M (2008) Structural equation modeling: guidelines for determining model fit. Electron J Bus Res Methods 6(1):53–60

Hope D, Gries C, Zhu W, Fagan WF, Redman CL, Grimm NB, Nelson AL, Martin C, Kinzig A (2003) Socioeconomic drive urban plant diversity. Proc Natl Acad Sci 100(15):8788–8792

Huang G, Zhou W, Cadenasso ML (2011) Is everyone hot in the city? spatial pattern of land surface temperatures, land cover and neighborhood socioeconomic characteristics in Baltimore City, MD. J Environ Manag 92(7):1753–1759

Jenerette GD, Harlan SL, Brazel A, Jones N, Larsen L, Stefanov WL (2007) Regional relationships between surface temperature, vegetation, and human settlement in a rapidly urbanizing ecosystem. Landscape Ecol 22:353–365

Jenerette GD, Harlan SL, Stefanov WL, Martin CA (2011) Ecosystem services and urban heat riskscape moderation: water, green spaces, and social inequality in Phoenix, USA. Ecol Appl 21(7):2637–2651

Johnson DP, Stanforth A, Lulla V, Luber G (2012) Developing an applied extreme heat vulnerability index utilizing socioeconomic and environmental data. Appl Geogr 35:23–31

Kline RB (2010) Principles and practice of structural equation modeling, 3rd edn. The Guilford Press, New York

Klinenberg E (2002) Heat wave: a social autopsy of disaster in Chicago. University of Chicago Press, Chicago

Lei PW, Wu Q (2007) Introduction to structural equation modeling: issues and practical considerations. Educ Meas Issues Pract 26(3):33–43

Li X, Zhou W, Ouyang Z (2012) Spatial pattern of greenspace affects land surface temperature: evidence from the heavily urbanized Beijing metropolitan area, China. Landscape Ecol 27:887–898

Oke TR (1982) The energetic basis of the urban heat island. Q J R Meteorol Soc 108(455):1–24

Oke TR (1995) Classics in physical geography revisited—Sundborg A. 1951: climatological studies in Uppsala with special regard to the temperature conditions in the urban area. Prog Phys Geogr 19:107–113

Oke TR (2006) Towards better scientific communication in urban climate. Theor Appl Climatol 84(3):179–190

Polsky C, Grove JM, Knudson C, Groffman PM, Bettez N, Cavender-Bares J, Hall SJ, Heffernan JB, Hobbie SE, Larson KL, Morse JL (2014) Assessing the homogenization of urban land management with an application to US residential lawn care. Proc Natl Acad Sci 111(12):4432–4437

Reid CE, O'Neill MS, Gronlund CJ, Brines SJ, Brown DG, Diez-Roux AV, Schwartz J (2009) Mapping community determinants of heat vulnerability. Environ Health Perspect 117(11):1730–1736

Romero-Lankao P, Qin H, Dickinson K (2012) Vulnerability to temperature-related hazards: a meta-analysis and meta-knowledge approach. Glob Environ Change 22(3):670–683

Schwarz K, Fragkias M, Boone CG, Zhou W, McHale M, Grove JM, O'Neil-Dunne J, McFadden JP, Buckley GL, Childers D, Ogden L (2015) Trees grow on money: urban tree canopy cover and environmental justice. PLoS ONE 10(4):e0122051

Uejio CK, Wilhelmi OV, Golden JS, Mills DM, Gulino SP, Samenow JP (2010) Intra-urban societal vulnerability to extreme heat: the role of heat exposure and the built environment, socioeconomics, and neighborhood stability. Health Place 17:498–507

Wilhelmi OV, Hayden MH (2010) Connecting people and place: a new framework for reducing urban vulnerability to extreme heat. Environ Res Lett 5(1):14–21

Wolch JR, Byrne J, Newell JP (2014) urban green sace, public health, and environmental justice: the challenge of making cities 'just green enough'. Landsc Urban Plan 125:234–244

Zhou W, Huang G, Cadenasso ML (2011) Does spatial configuration matter? Understanding the effects of land cover pattern on land surface temperature in urban landscapes. Landsc Urban Plan 102(1):54–63

Zhou W, Troy A (2008) An object-oriented approach for analyzing and characterizing urban landscape at the parcel level. Int J Remote Sens 29:3119–3135