Investigating contributing and mitigating factors of land surface temperatures in the Los Angeles River Watershed

Riley Blasiak[1,4]; Katie Spahr[2,4], PE, PhD; Anneliese Sytsma [3,4]

[1]University at Buffalo, Department of Civil, Structural and Environmental Engineering, [2]Colorado School of Mines, Department of Civil and Environmental Engineering, [3]University of California, Berkeley, College of Environmental Design, [4]Re-Inventing the Nation's Urban Water Infrastructure (ReNUWIt)

Introduction

The amount and severity of heat waves are predicted to continue to increase over this century, resulting in higher summer temperatures and lower soil moisture [1]. The increase in extreme heat events has led to higher mortality rates in urban areas around the world: for example, in Berlin, Germany the highest mortality rates occurred within the most densely urbanized sections of the city [2]. Urban heat island (UHI) is the phenomenon that urban areas have higher atmospheric and land surface temperatures than rural areas. These higher temperatures, in turn, increase air conditioning demands and air pollution levels, and modify precipitation patterns [3].

However, UHI is difficult to map and quantify due to the spatial and temporal resolution of the data available. Consequently, recent research has looked into land surface features that are correlated with UHI, such as impervious surfaces, normalized difference vegetative index (NDVI), canopy cover, land slope, and roof surfaces [4], while other research has focused on the potential to mitigate the negative impacts of UHI with urban greening [5-7]. The Los Angeles River (LAR) watershed in Los Angeles, California presents a unique opportunity to study UHI and urban greening mitigation measures due to its extensive impervious area, hot climate, and stormwater quality initiatives [8]. This study (1) investigates the relationships between land surface features and land surface temperature (LST), and (2) identifies high priority areas for urban greening within the LAR watershed.

Methods

Data acquisition and pre-processing

Based on previous studies, we hypothesized that land surface temperature (LST) in the LAR watershed was correlated to percent impervious area, percent canopy cover, percent roof area, mean NDVI, and mean land slope. We acquired these data (LST, impervious surfaces, canopy cover, roofs, NDVI, and slope) through the Los Angeles County planning department, research colleagues, and Landsat 8 imagery processed in Google Earth Engine (GEE)[9].

Due to variable spatial resolution in the source data the spatial data needed to be summarized on consistent scales, (subwatersheds) and converted to the correct format (shapefiles). To summarize the variables by subwatersheds, the mean area (land slope, NDVI) or area relative to total subwatershed area (impervious, canopy cover, roof surfaces) within each subwatershed was calculated using the zonal statistics tool in ArcGIS. The resulting raster files were then converted into shapefiles for analysis.

Regression analysis

Prior to conducting a formal regression analysis, we confirmed that these variables were visually related to LST by mapping them in ArcMap. To evaluate all the variables in a single regression analysis, each shapefile was combined into a single shapefile using the spatial join tool in ArcGIS. Excel was used to plot all the variables versus each other in order to identify any multicollinearity and verify independence between variables.

Ordinary least squares (OLS) was used to determine the relationships between all the variables and LST. The OLS model originally included all variables that were hypothesized to impact LST: percent impervious, percent canopy cover, and percent roof surfaces (buildings), mean NDVI, and mean land slope. The statistically significant relationships (i.e. $p < 0.01$) were determined and explored with the spatial statistics tools in ArcGIS. Due to many of the selected variables not being significant, an exploratory regression test was run. In this test the relationship between all the variables was explored.

Suitability analysis

Following the statistical analysis, a suitability analysis was conducted to prioritize locations for green infrastructure that would have multiple co-benefits: reducing LST, improving stormwater quality, and benefiting high risk demographics. During the analysis, green infrastructure was assumed to be beneficial in areas with poor stormwater quality, higher LST, large amounts of impervious areas, low amounts of vegetation, and high-risk demographics. Stormwater quality data included median E. coli and total suspended solids (TSS) concentrations, created from data provided by California Environmental Data Exchange Network (CEDEN). The demographic data was acquired from the 2016 American Community Survey, and included low income households (lower than $54,250 per year [10]), people over the age of 65, and people under the age of five [11]. Thresholds for all the variables were determined by summarizing the variables for each Census Tract in the LAR and then using the median of the tract values as the cut off value (*Table A-1*). After we determined these thresholds, the spatial join tool in ArcGIS was used to combine the shapefiles into a single shapefile.

Three screening levels were defined to reduce the number of high priority tracts. The first level included big picture problems: stormwater quality (E. Coli and TSS) and LST. The second level incorporated physical land characteristics (impervious surfaces, canopy cover, NDVI and parks) in addition to the first level variables. The third level, which identifies where green infrastructure could have the most co-benefits, incorporated demographics and was used to determine the highest priority tracts, these tracts included: high LST, high E. Coli, high TSS, high impervious, low vegetation, low parks, low canopy, and more high-risk demographics.

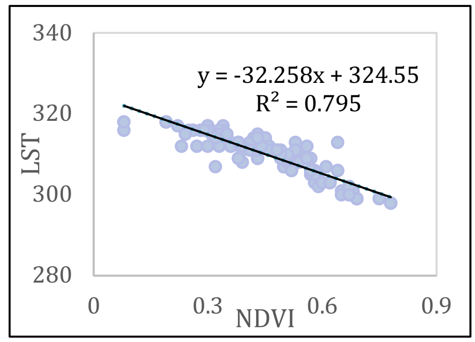

Figure 1: Graph of greenness vs land surface temperature with final regression equation

Results

Results of the regression analysis show that NDVI alone accounts for 79% of the variation in LST *(Figure 1*), and adding more variables only marginally improves the explanatory power to 82% (*Table A-2*). Furthermore, we found that many of the independent variables were related to each other (e.g., NDVI and impervious surfaces), thus, choosing NDVI alone avoids any issues of multicollinearity. Overall, we found that NDVI alone is capable of predicting the spatial distribution of LST, and of identifying locations where UHI phenomenon exists.

Results of the suitability analysis show that of the 1068 total tracts, 215 were identified as level one tracts and 107 as level two tracts. The number of level three tracts, which included the demographic data, physical land characteristics and stormwater quality, was reduced to 57 highest priority tracts. Implementing green infrastructure in these 57 high priority tracts could improve LST, water quality, greenness, and benefit high risk demographics (*Figure 2*).

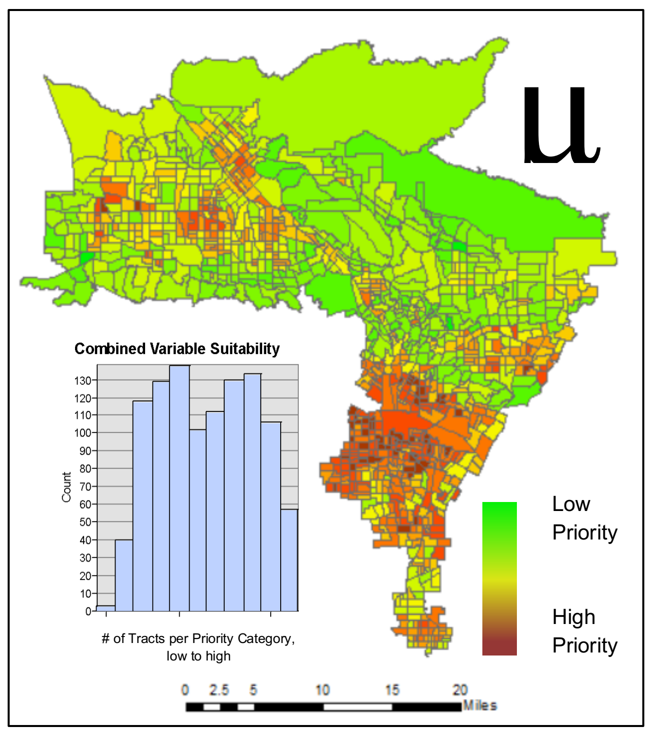

Figure 2: Map of LAR watershed showing high priority tracts for green infrastructure implementation

Conclusions

This study found that NDVI accounts for 79% of the variation in LST in the LAR watershed. As NDVI (greenness) increases, LST decreases, suggesting that implementing green infrastructure will further reduce LST. We found that 57 tracts should be considered high priority for green infrastructure implementation. Green infrastructure may improve LST as well as stormwater quality, reduce impervious surfaces and vulnerability of populations in these tracts. Future work should collect data to examine how green infrastructure benefits certain tracts and populations in the LAR watershed. Similar studies should be implemented around the US and the world throughout the year to verify the findings outlined above.

Sources

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Appendix

Table A-1: Threshold values for each variable with associated screening levels

Variables	Threshold	
LST	>	315.6 K
E. coli	>	3644.1 MPN/100ml
TSS	>	26.34 mg/L
NDVI	<	0.33
Impervious	>	65%
Canopy	<	17%
Parks	<	0.10%
Younger than 5	>	6.10%
Older than 65	>	11.50%
Low income	<	$54,250

Level 1

Level 2

Level 3

Table A-2: OLS results

	Run1			Run 2			Run3			Run 4		
	p-value	R^2	VIF	p-value	R^2	VIF	p-value	R^2	VIF	p-value	R^2	VIF
NDVI	0.00*		5.568	0.00*		5.25	0*		3.646	0.00*	0.79	1
Impervious	0.91		10.45	0.00003*		7.699	0.000013*	0.821	3.646			
Buildings	0.787		5.387	0.15		5.24						
Canopy cover	0.055		1.62	0.37	0.82	1.61						
Slope	0.00*	0.824	4.186									