Understanding Efficient Mitigation Strategies for Los Angeles' Heat Islands using OLS Regression Analysis

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ABSTRACT: As architects design the cities of the future, the climatological impact of the built environment must be considered. Previous research has shown that the Urban Heat Island (UHI) effect is exacerbated by the presence of impervious surfaces and mitigated by cooling features such as urban forestry, water features, and vegetation (Ruiz-Avilles, 2020), (Hoffman, 2020). Through the analysis of satellite imagery of Los Angeles County, this study expands the scope of UHI research by creating regression models to explain the relative impact of multiple variables on land surface temperature. These variables include impervious surface, water, forestry, vegetation, and surface reflectance among others in Part I. Preliminary results indicate that increasing the density of impervious surface development is associated with higher temperatures while the presence of vegetation, tree canopy, and water reduces temperature significantly. In Part II, the researchers calculate the economic cost of poor UHI mitigation by estimating the cost of mechanical cooling to achieve occupant comfort. The purpose of this estimation is to quantify the financial benefit associated with implementing naturally cooling designs in new and existing buildings. Part II also includes suggestions for design strategies intended to optimize heat mitigation based on our findings.

KEYWORDS: regression analysis, Urban Heat Islands, land surface temperature, cooling design, cost analysis

PAPER SESSION TRACK: Global Sustainability: Mitigation and Adaptation

INTRODUCTION

Continued expansion and development of urban spaces is inevitable with a growing global population. Research also shows that the intensity, duration, and frequency of heat waves in Los Angeles are increasing as the effects of global climate change continue (Perkins-Kirkpatrick, 2020). Taking these two unavoidable truths into consideration, architects have a responsibility to design their projects with a substantial focus on limiting the Urban Heat Island (UHI) effect around their designs. The UHI effect describes the phenomenon of urban areas having significantly higher temperatures than surrounding rural areas. This is caused by a variety of factors including a lack of vegetation and shade from tree canopy, incidence of impervious surfaces such as asphalt and concrete that increase surface and ambient temperature, and many others (Abbas, 2017). Extreme heat can have devastating effects on many facets of life, from increases in heat related deaths to wildfires to overwhelming power grid demand (Burillo, 2019) (Bartos, 2014). Extreme heat is uncomfortable for Los Angeles residents and disproportionately impacts lower income communities (Bartos, 2014). If architects are able to effectively design buildings to control the surrounding and internal temperature, the results of this study demonstrate that this could have a legitimate impact on mitigating the UHI effect. The heat map used to build the regression models and inform the conclusions of this project is shown in Figure 1. The entire study area was subsequently partitioned into smaller sample areas which are also shown in Figure 1. The high desert area of Los Angeles County was not sampled because the area is not as densely developed as the central, southern, and western parts of the county and therefore is not as strong of a candidate for urban infrastructure intervention to mitigate heat.

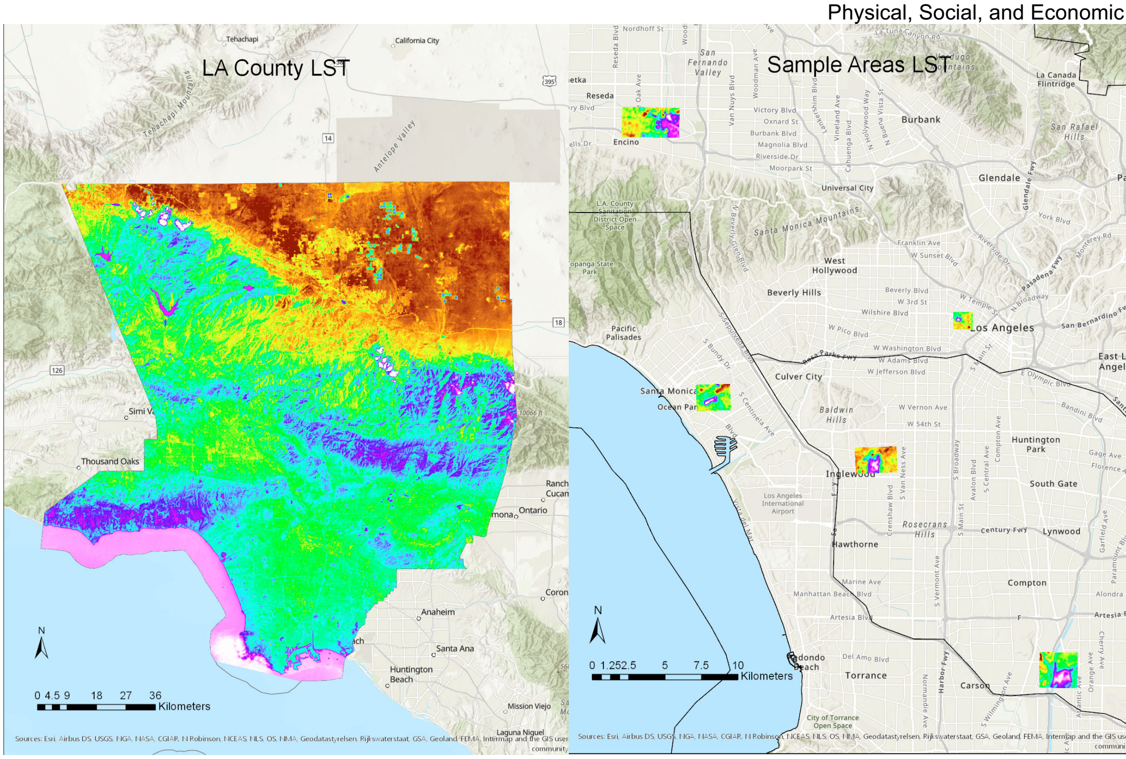

Figure 1: Land surface heat map of the entire study area from which the samples are drawn and used to create representative regression models (L). Heat maps of the sampled areas, also showing Climate Zone boundaries (R).

1.0 LITERATURE REVIEW AND DATA PREVIEW

1.1 Existing Research

The goal of this study is to assess the Urban Heat Island effect through a multidisciplinary approach providing specific recommendations at the urban and architectural scale. Most of the existing literature looks at a single factor influencing the distribution of land surface temperature. Many studies specifically examine the relationship between historical divestment in low-income, minority communities and higher temperatures (Hoffman, 2020). In "The Effects of Historical Housing Policies on Resident Exposure to Intra-Urban Heat: A Study of 108 U.S. Urban Areas", the authors show that historically redlined neighborhoods are more likely to experience hotter temperatures due to a lack of green spaces and mature tree canopy to provide shade (Hoffman, 2020). However, green space and tree canopy are not the only factors involved in cooling an area. As seen in "Mitigation of Urban Heat Island Effects through 'Green Infrastructure': Integrated Design of Constructed Wetlands and Neighborhood Development", constructed wetlands and water features in traditionally dry climates that do not naturally support forestry can also lead to a cooling effect and reduction of urban heat islands (Ruiz-Aviles, 2020). Multiple other studies such as "Low carbon districts: Mitigating the urban heat island with green roof infrastructure" support the hypothesis that adding green infrastructure or green space to existing urban areas can mitigate the urban heat island effect (Lehmann, 2014). There is an established, statistically significant relationship between increased Normalized Difference Vegetation Index (NDVI) caused by live vegetation and lower summer surface temperatures (Kaufmann, 2003). The authors of "Low carbon districts" specifically state that although green roofs are a potential solution to the urban heat island effect due to their established temperature controlling properties, they do not always contribute to native biodiversity (Lehmann, 2014). This issue is addressed by this study's unique micro-sampling approach to determine the specific needs of various climates within Los Angeles. Notably lacking from the existing lexicon of research on this topic is a methodology that seeks to understand the combined effect of these known warming and cooling factors. As a result, studies without a diverse set of variables can contribute to a biased result. Omitted variable bias leads to either over or understating the impact of a variable of interest on the dependent variable (Omitted Variable Bias: Wald Test, 2021). This study also seeks to account for the many climates included within Los Angeles County, which differs from the methodologies of existing, similar studies that tend to assess an entire city through an internally comparative lens.

1.2. Data

Existing scientific literature informs this study's choices of explanatory variables, as well as the data sources used. Based on a thorough literature review process, the researchers decided to include land cover type, infrared reflectance, near infrared reflectance, short wave infrared reflectance, and distance to roads as explanatory criteria for the dependent variable land surface temperature. The three reflectance types reflect the albedo effect and account for the presence of vegetation, which can be left out of the land cover type dataset due to the nature of the source. To calculate Land Surface Temperature and Reflectance, the researchers used Landsat8 imagery sourced from the United States Geological Survey (USGS). Landsat8 images were only considered if they included cloud cover of less than 10% and if they were recorded during the daylight hours of the summer months. Using a 10% threshold for cloud cover is consistent with the study design in existing literature (Dialesandro, 2021), (Hoffman, 2020). The presence of clouds has a cooling effect on temperature during the day, and a warming effect at night which can result in inaccurate land surface temperature calculations as well as a complete inability to calculate the land surface temperature or surface reflectance for areas that are obscured partially or completely (Jeppesen, 2019). Vegetation has a cooling effect on summer temperatures and a warming effect on winter temperatures (Bumseok, 2018). This study focuses on determining the most efficient heat mitigation strategies, so it makes sense to assess only summer months. The extreme temperatures associated with the summer months provide more relevant information with regards to the economic cost of extreme heat events when mitigation tactics are not employed. Land cover type data was sourced from the National Land Cover Database, while data showing all roads was sourced from Los Angeles' geodatabase portal LA Geohub. Climate Zone and LA County boundaries were also sourced from LA Geohub. The data used to calculate the economic cost of running low efficiency air conditioning units is based on the methodology in "Efficiency, economics, and the urban heat island" (Miner, 2017). This study quantified the costs of running low efficiency window AC units for Phoenix, AZ as well as other cities with a documented heat island effect. The authors used cooling degree days as estimated by the online tool Bizee Degree Days (Miner, 2017). Since the target estimation is similar, the methodology of this paper closely followed that of "Efficiency, economics, and the urban heat island". Estimations for the daily cost of running these low efficiency air conditioners as well as the proportion of households using window units instead of central air conditioning, which is more cost effective, comes from the Residential Energy Consumption Survey completed by the U.S. Energy Information Administration (RECS, 2015). Results are illustrative of potential impact and could be larger or smaller depending on the difference between estimated number and type of air conditioning units and actual numbers.

2.0 METHODS AND RESULTS

2.1. Methods

This study was completed in two parts, each with a distinct workflow and methodology. Part I was completed using ArcGIS Pro and R statistical software. Figure 2 shows the methodology workflow of Part I which begins with loading all the relevant data sets into ArcGIS Pro using a 30x30m pixel size. The study uses the Projected Coordinate System NAD 1983 UTM Zone 11N. California is designated into 16 Climate Zones, each representing a different microclimate. LA County includes five of these climate zones, and this study samples the three prominent ones. Climate Zone 6 includes the milder coastal region, while Zones 8 and 9 include warmer inland areas. These sample areas were chosen where the researchers observed a diverse selection of roads, urban infrastructure, and vegetation. Small-scale samples allow the regression to be performed at the pixel level (30x30m). Samples were only considered if the observed elevation is roughly homogenous, as large changes in elevation over a short physical distance can impact surface reflectance. Equations (1)-(7) specify the functions used to calculate Land Surface Temperature (LST) and surface reflectance.
Top of Atmosphere spectral reflectance (L) is found using equation (1).

(1) $L = M_L * Q_{cal} + A_L$

Where M_L is the band specific multiplicative rescaling factor as written in the metadata documentation, Q(cal) is the Thermal Band (Band 10), and A_L is the Band specific additive rescaling factor as written in the metadata. The results from this calculation are then used to calculate the Brightness Temperature adjusted from Kelvin to Celsius. This is found with equation (2).

(2) $BT = (K_2 / (\ln (K_1 / L) + 1)) - 273.15$

Where K_1 and K_2 are both band specific thermal conversion constants stated in the metadata, and L is the TOA Spectral Reflectance previously calculated. Then, we calculated the Normalized Difference Vegetation Index (NDVI) using Band 4 (Infrared) and Band 5 (Near Infrared) in equation (3).

(3) $NDVI = (Band\ 5 - Band\ 4) / (Band\ 5 + Band\ 4)$

The NDVI is closely related to the Percent Vegetation (P_v), which we calculate using equation (4).

(4) $P_v = [(NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min})]^2$

P_v is used to calculate emissivity (ε), which is the final step needed before calculating LST. ε is found using equation (5).

(5) $\varepsilon = 0.004 * P_v + 0.986$

The value of 0.986 is a correction value for the equation. Finally, LST is calculated using equation (6).

(6) $LST = (BT / (1 + (0.00115 * BT / 1.4388) * \ln(\varepsilon)))$

To calculate Infrared Reflectance, Near Infrared Reflectance, and Short-Wave Infrared Reflectance, this study uses the same Landsat8 imagery using the Infrared, Near Infrared, and Multispectral bands and equation (7).

(7) $[(DN * 0.00002) - 0.1] / \cos(S_z)$

Where DN indicates the band specific digital number, 0.00002 is the band specific multiplicative reflectance rescaling factor, -0.1 is the band specific additive reflectance rescaling factor, and S_z is the solar zenith angle as written in the metadata.

To prepare the raster data for regression, the land cover type codes from the NLCD were converted into indicator variables. The base case indicator variable is impervious surface with an impervious surface/vegetation split of less than 20% impervious surface, greater than or equal to 80% vegetation or undeveloped open space. The models were estimated using Ordinary Least Squares regression and then select variables were standardized using a standardized beta coefficient for interpretation. Table 3 shows the standardized beta coefficients for the surface reflectance explanatory variables within each sample.

Table 1: Description of the explanatory variables used in the regression models

Variable	Description	Example	Source
Land Cover Type Indicators (specified below)	For each land cover type present in the sample area, the land cover indicators take on a value of either 0 or 1 if the 30x30m unit of analysis is classified as the respective land cover type	Water, Herbaceous Wetland, Shrub/Scrubs, Mixed Forest, Impervious Surface	National Land Cover Database (NLCD)
Near Infrared Reflectance (NR)	Near Infrared Reflectance is a measure of surface reflectance and increases with the presence of vegetation.	Golf courses, urban forestry, parks, living roofs, tree lined streets, landscaped medians, living walls	Landsat8 imagery
Shortwave Infrared Reflectance (SR)	Shortwave Infrared Reflectance is a measure of surface reflectance that is commonly used to assess mineral content, as well as soil moisture.	Minerals in rocks or other reflective surfaces	Landsat8 imagery
Infrared Reflectance (RR)	Infrared Reflectance is a measure of surface reflectance and increases with the presence of impervious surface and other man-made materials	Asphalt, cement, metal, large buildings	Landsat8 imagery
Distance to Nearest Road (D)	The Euclidean distance in meters from the nearest road to a 30x30m unit of analysis		Los Angeles County Geohub Database

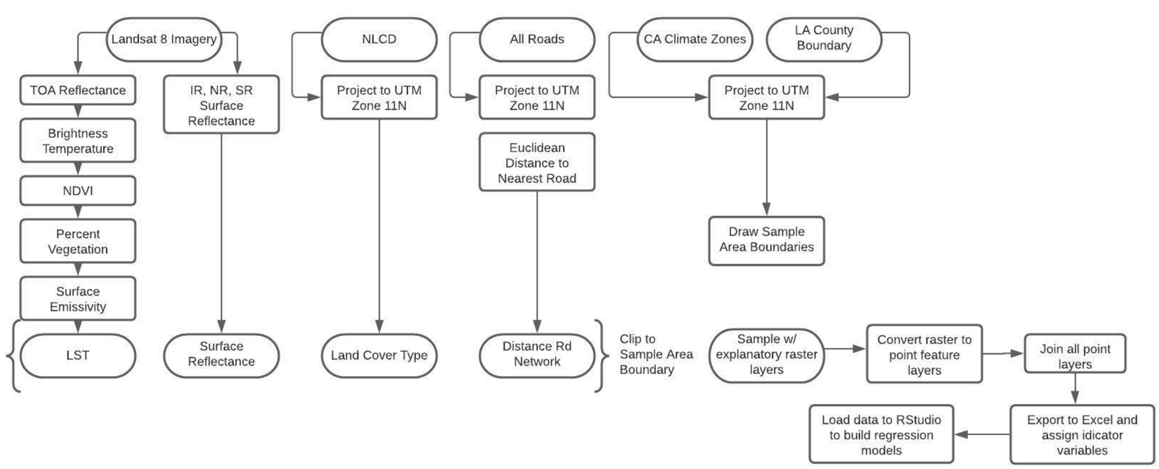

Figure 2: Part I Workflow Diagram showing the logical progression of determining the relative effect of existing elements on Land Surface Temperature.

In Part II, the workflow diagram specifies a simple arithmetic approach to estimate the costs of running low-efficiency air conditioners annually in the three climate zones of Los Angeles that were incorporated in the regression. This was the focus of the cost analysis because reducing the incidence of these low efficiency AC units is a feasible goal that would require investment in small scale design choices like living roofs to passively cool a residential or commercial space through indirect and direct impacts. To estimate the cost of this usage, the researchers calculated the number of households within each climate zone that are currently using window AC units using demographic data from the U.S. Census, Climate Zone boundaries, and AC data from the 2015 Residential Energy Consumption Survey (Residential Energy Consumption Survey, 2015). Figure 3 shows the workflow for Part II.

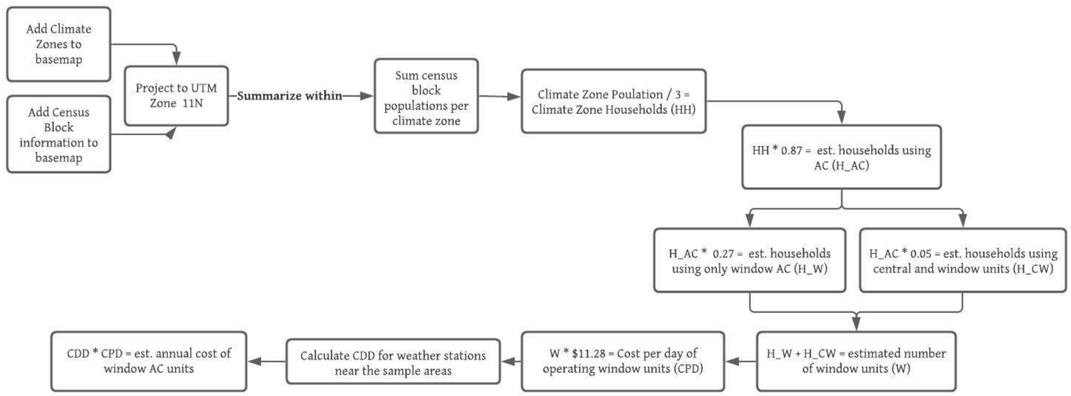

Figure 3: Workflow diagram for Part II methodology: Approximate the cost of AC usage for each Climate Zone to estimate consumer savings potential with widespread implementation of living roofs.

2.2. Results

In ArcGIS, the raster layers representing each of the explanatory variables clearly indicate patterns in LST. Figure 4 shows the explanatory layers juxtaposed next to LST for the San Fernando Valley (SFV) sample as an example of the ArcGIS results seen in all five samples. Assessing the heat map image relative to the explanatory factors in the following layers, there is a clear halo effect of cooling surrounding particularly effective features such as the golf course, lake, and naturally banked LA river. The relatively cool spots generated by the cooling features extends beyond their physical boundaries, resulting in a cooler land surface temperature for the immediately surrounding area regardless of the factors present there. This observation indicates that the benefits of designing living infrastructure extend beyond the physical extent of the design itself and can be strategically placed to optimize the general cooling impact. The opposite effect is true for warming features such as dense impervious surface development as seen following the 101-freeway running from the top to the middle right side of the sample and within the residential neighborhood without significant green space in the bottom left corner of the sample.

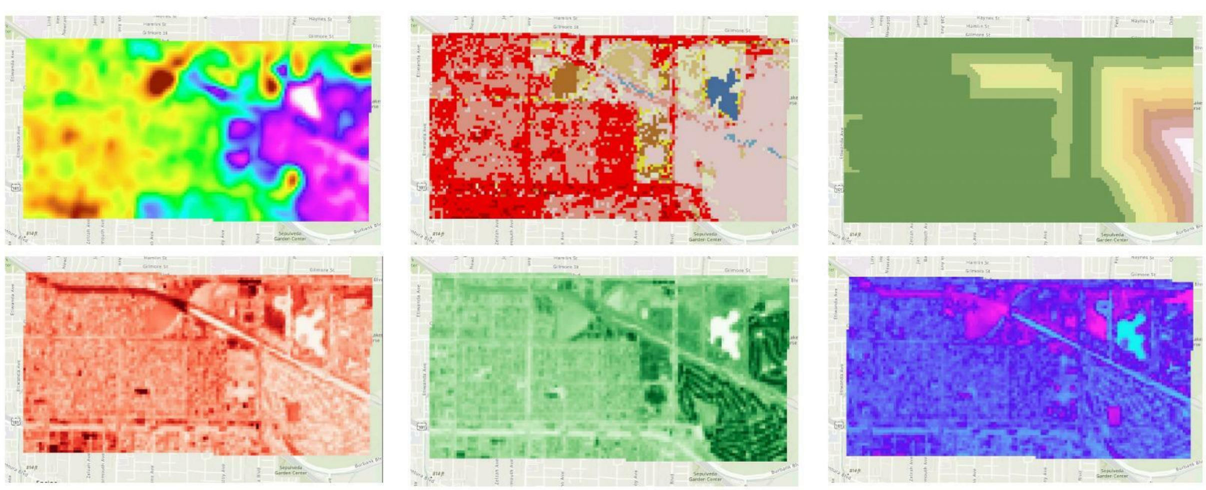

Figure 4: ArcGIS raster layers example clockwise from left: Land Surface Temperature; Land Cover Type; Distance to Nearest Road; Shortwave Infrared Reflectance; Near Infrared Reflectance; Infrared Reflectance

For each of the five samples, the resulting regression model quantifies the relationship between the existing urban design elements and land surface temperature as it varies across the surface area of each sample. Since there are both continuous and binary explanatory variables included the model, the models are interpreted first using the traditional coefficient estimates and then they are standardized to interpret the continuous variables specifically. Table 2 describes the samples for which there are two regression models.

Table 2: Sample Areas, their abbreviation, and Climate Zone represented

Sample Name	Abbreviation	Climate Zone
Santa Monica	SM	6

North Long Beach	NLB	8
Inglewood	ING	8
Downtown LA	DTLA	9
San Fernando Valley	SFV	9

The regression models are shown in equations (8) through (12):

(8) $T_{SM} = 31.49 + .008D + 5.895RR - 10.667NR + 8.978SR + 0.91IS_{50} + 1.129IS_{80} + 1.519IS_{100} + 1.462S + 0.241P + \varepsilon$

(9) $T_{NLB} = 32.297 - 0.006D + 8.274RR - 10.606NR + 6.617SR + 0.347IS_{50} + 1.448IS_{80} + 2.327IS_{100} - 0.455S + 1.638P + 0.8H - 2.534E - 0.143W + \varepsilon$

(10) $T_{ING} = 33.283 + 0.005D + 10.075RR - 12.830NR + 3.734SR + 0.848IS_{50} + 1.44IS_{100} + 1.479IS_{81} + 0.947S + 0.876P + 0.571H + \varepsilon$

(11) $T_{DTLA}=33.102+0.002D+4.846\ RR-8.746NR+6.801SR+1.712IS_{50}+2.341IS_{80}+2.613IS_{100}-3.288W + \varepsilon$

(12) $T_{SFV} = 34.065 - 0.003D + 4.955RR - 9.304NR + 14.099SR + + 0.822IS_{50} + 0.995IS_{80} + 1.531IS_{100} + 0.526S - 0.437P + 0.387H - 3.113W - 0.571HW + \varepsilon$

Where:
T_{xxx} = Sample Land Surface Temperature
D = Euclidean Distance to nearest road
RR = Infrared Reflectance
NR = Near Infrared Reflectance
SW = Shortwave Infrared Reflectance
IS_x = Impervious Surface / Vegetation mix <= x%
S = Shrub / Scrub Land Cover
P = Pasture Land Cover
H = Herbaceous Land Cover
E = Evergreen Forest Land Cover
W = Open Water Land Cover
HW = Herbaceous Wetland Land Cover

These regression models fit the data well, with adjusted R-squared values ranging from 0.500 to 0.778. In the case of the San Fernando Valley sample (Figure 4), increasing the mix of impervious surface and open space to be between 21 and 50% (IS_{50}) is associated with an increase of 0.822 degrees Celsius on average compared to areas with less than 20% impervious surface. Further increasing the percent of impervious surface within the 30x30m area to between 51 and 80% (IS_{80}) is associated with an increase of 0.995 degrees Celsius on average compared to again to the omitted indicator case. Areas with between 81 and 100% impervious surface are associated with an average increase of 1.531 degrees Celsius as compared to the base case indicator. This pattern is consistent throughout the other sample areas as well. The average temperature increases relative to the base case as the amount of impervious surface increases. This consistency across the samples is what indicates that the percent area covered by impervious surfaces is a critical variable to consider when planning and designing new urban infrastructure. The base case indicator allows for some necessary development while prioritizing the open space, vegetation component.

Table 3: Standardized Beta Coefficients of the models

Sample	**RR**	**NR**	**SW**
SM	0.1521	-0.4668	0.1903
NLB	0.2267	-0.3874	0.1523
ING	0.2032	-0.4684	0.0805
SFV	0.0781	-0.3451	0.2944
DTLA	0.1219	-0.2702	0.1481

The standardized Beta coefficients not only simplify the interpretation process, but also indicate the relative impact of each of the explanatory variables on land surface temperature as compared to each other. A variable with a larger standardized beta coefficient in absolute value has a larger impact on LST than other variables. Consistently, Near Infrared Reflectance has a cooling effect on temperature as seen in Table 4. Increasing the Near Infrared Reflectance of a 30x30 meter by one standard deviation decreases land surface temperature by 0.4668 standard deviations in Santa Monica, 0.3874 standard deviations in North Long Beach, 0.4684 standard deviations in Inglewood, 0.3451 degrees in the San Fernando Valley, and 0.2702 standard deviations in Downtown LA on average. Increasing Near Infrared Reflectance by one standard deviation also has a relatively stronger impact on land surface temperature than Infrared Reflectance or Shortwave Infrared Reflectance also as noted in Table 4. Infrared Reflectance is associated with larger amounts impervious surfaces and other man-made development while Near Infrared Reflectance is increased by adding vegetation to the area.

Both the traditional linear model and the standardized beta coefficients show a few variables with consistent impact on land surface temperature across the samples and regardless of the surrounding environment. These are referred to in this study as strong indicators of heating and cooling effects and are summarized in Table 4. Negative values indicate features with a cooling impact on LST, while positive values indicate a feature with warming properties. Therefore, more negative values are preferable, while positive values should be reduced by employing heat conscious design strategies.

Table 4: Strong indicators of cooling or warming. Variables marked with * are standardized beta coefficients.

Variable	SM	NLB	ING	SFV	DTLA
RR*	0.1521	0.2267	0.2032	0.0781	0.1219
NR*	-0.4668	-0.3874	-0.4684	-0.3451	-0.2702
SW*	0.1903	0.1523	0.0805	0.2944	0.1481
IS_{50}	0.91	0.347	0.848	0.822	1.712
IS_{80}	1.129	1.448	1.44	0.995	2.341
IS_{100}	1.519	2.327	1.479	1.531	2.613
W	--	-0.143	--	-3.113	-3.288

Strong indicators of LST include Infrared, Near Infrared, and Shortwave Infrared Reflectance, all three designations of impervious surfaces, and water. According to the coefficient value for water shown in Equation 9 as well as in Table 4, areas in that sample (NLB) were only 0.143 degrees cooler on average than the base case. This is in stark contrast to the impact of water in the San Fernando Valley sample, where areas of water were on average 3.113 degrees cooler than the base case indicator. Similarly, in the Downtown LA sample, areas of water were on average 3.288 degrees cooler than the base case. The discrepancy between the cooling effect of water in North Long Beach and the other samples points out the importance of surrounding development in creating effective temperature control. In North Long Beach, the banks of the LA River are replaced by a cement canal. The surface reflectance and heat generated by this high concentration of impervious surface counteracts the cooling effect of water in the area. This indicates that simply developing water features without a commitment to also restoring natural herbaceous wetland, wetland, or other vegetation is an inefficient cooling strategy. Water is much more effective at cooling the local area when paired with natural elements such as herbaceous wetland natural banking.

The estimated cost of the air conditioning usage reflects consumer spending on climate control. The lowest customer expenditure is in the coastal climate zone (Zone 6), while the two inland zones have higher estimated levels of spending. AC usage also impacts public spending as power grid demand increases on days of extreme heat if buildings are not designed in a way to effectively control the climate without the use of air conditioning. Empirically proven, quantitative data with a direct link to potential cost savings has the potential to be very convincing in the planning stages of a project. Increasing the specific cooling features in an area by designing living roofs, walls, and naturally banked water features is linked to cooler temperatures, which reduce the number of cooling degree days where AC units must be used.

3.0 CONCLUSION

Based on these results, the most efficient cooling design strategies in all LA Climate Zones are those that increase Near Infrared Reflectance through vegetation. In special cases, water features can also be a major cooling factor. This can be incorporated into building designs by adding a living roof, living wall, or other urban forestry such as courtyards and tree lined streets and walkways. Unlike vegetation, which has a universally efficient cooling impact, the cooling efficiency of water is conditional upon the surrounding infrastructure. In less densely populated regions of LA County, focusing on restoration efforts of wetland areas will increase existing water features' cooling impact, and will also increase the amount of Near Infrared Reflectance by introducing vegetation. Wetland rehabilitation and designs that seek to preserve native wetland or coastal vegetation should be of particular focus in Climate Zone 6, which benefits from a less dense urban sprawl and is directly adjacent to the Pacific Ocean. For all climate zones, the preferred cooling strategy of the authors is incorporating a green roof with a focus on increasing passive cooling and native biodiversity in the design. Living building elements, such as green roofs and green walls, can naturally insulate a building, making the inside climate more likely to be habitable without the use of an air conditioner (Miner, 2017), (Lehmann, 2014), (Bumseok, 2021). Extensive research by Pablo LaRoche on the technical design and implementation of efficient green roofs has been done. His designs focus on the direct cooling impact of a green roof with respect to thermal comfort and a reduced need for air conditioning (LaRoche, Yeom, 2019). The results of this study show that green roofs also have an indirect cooling impact by increasing the amount of Near Infrared Reflectance and therefore providing an efficient means of general temperature control to the area. When the use of impervious surfaces is necessary, designs should prioritize at least a less than 50% split between impervious surface and open space (ideally filled with native species of vegetation). Designs that keep the impervious surface/ open space split less than 20% are ideal when possible. This can be achieved through the integration of vegetation into the architecture of the building. Again, this is best achieved using biodiverse living roofs, especially in areas that are already developed (La Roche, Yeom, 2019).

The results of this study demonstrate that increasing vegetation in an area has a relatively stronger impact on land surface temperature than increasing impervious surfaces. This is a positive indicator in the pursuit of true mitigation of the urban heat island effect. With a universal commitment to incorporating living designs into the architecture of new and existing buildings, efficient urban cooling is possible at a micro and macro level.

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