Assessing Urban Vegetation as an Urban Heat Island Effect Mitigation Strategy in Berkeley and Oakland, California

Mirit Friedman

ABSTRACT

The conversion of natural vegetated landscapes into impervious surfaces causes a shift in the urban climate know as the Urban Heat Island (UHI) Effect. The magnitude of and mitigation strategies for this phenomenon are place specific. The projected population increase in the San Francisco Bay Area will likely prompt further relative warming of local urban centers. This study aimed to understand whether vegetation in Bay Area park spaces can be a net positive mitigator of UHIs. Using atmospherically corrected Landsat imagery of parks from nine dates in 2014, I built linear regression models of each month to look at the overall trends of how Normalized Difference Vegetation Index (NDVI) values correlate with thermal intensity values, which are a proxy for surface temperature. To better understand the year-round dynamics of urban vegetation and ground-level temperature, I performed a pair-wise comparison of the slopes across seasons. Regression analysis suggests a negative relationship between NDVI and thermal intensity; increased incidence of green vegetation is associated with lower surface temperatures ($r^2 = 0.20$). Further, I found a marginally significant difference among the slopes of the different seasons, with the strongest association between variables occurring in summer. While these findings suggest that urban vegetation can be effective in mitigating the UHI Effect, particularly in summer, when temperatures are highest, further study is required to explore what types of vegetation would increase this net positive effect in addition to the best ways to design future parks to enhance UHI mitigation.

KEY WORDS

Normalized Difference Vegetation Index, Thermal Intensity, Urban Planning, GIS, Landsat

INTRODUCTION

Higher urban temperatures in mid- and high-latitude cities than in surrounding rural areas is widely known as the Urban Heat Island (UHI) effect (Taha 1997). This temperature differential is largely attributed to the historic discovery that the increased vertical dimension of cities such as taller buildings promotes an increased absorption of latent heat, furthermore increasing the average temperatures of cities (Howard 1833). Changes in land-cover, from open grasslands and woodlands to built cities increases the amount of impervious surfaces and simultaneously decreases natural vegetation and soil coverage (Simpson & McPherson 2007, Arnold and Gibbons 2007) thus decreasing the vegetative evaporative cooling process (Grimm et al. 2008). These ecological and climatic shifts, that have increased thermal intensity, have proven to also impact human well being (Jones et al. 2007). Prolonged exposure to elevated urban temperatures has been known to cause heat distress and higher mortality rates due to heat-driven atmospheric pollutant formation (Watkins et al. 2007). Additionally, higher thermal intensity increases peak summer energy demands for air conditioning buildings (Yuan and Bauer 2007) creating a positive feedback loop that relies on a continuously growing energy demand and subsequent temperature increases, ultimately perpetuating UHIs.

Understandings of the science concerning UHIs was slow to develop due to unknown site variability (Oke 1982) however, through large-scale satellite assessments of urban areas there have been improvements in the understanding of both UHIs and their potentially negative implications (Taha 1997; Voogt and Oke 2003). Because of the development of high-resolution, remotely sensed images, data can be used to increase the precision of land cover mapping, landscape analysis, and other factors (Huang et al., 2014). High-precision maps provide information on spatial and textural features, including vegetation cover assessment abilities and thermal analysis. With the improvement of this technology has come a greater understanding of surface-level influences on the UHI effect (Huang et al., 2014). Since the creation of the Landsat government satellites in 1983 (Landsat 1-8) studies have been able to use “more appropriate data for land cover analysis” (Haack 1987). Through access to seven or more bands that capture data along the electromagnetic spectrum within each satellite image, Landsat allows for the derivation of the Normalized Difference Vegetation Index value which measures the “greenness” of vegetative cover (i.e., its degree of photosynthetic and evapotranspirational activity) and thermal intensity. While the correlation between NDVI and thermal intensity has been explored previously, the studies are site specific and only explore single dates making the transferability of the results less significant.

The goal of this study was to apply the initial understanding of the negative relationship between NDVI and thermal intensity to parks in Berkeley and Oakland, California through the use of satellite imagery, in addition to understanding how this correlation changes in response to the seasonal shifts. This study focuses more specifically on parks as singular governmentally-defined entities to increase our understanding of parks beyond their recreational value, to assess their potential positive environmental benefits. Through a trans-temporal one-year study, the relationship between NDVI and thermal intensity can be further analyzed by seasonal trends. By understanding the seasonality of the cooling processes, further assumptions can be made regarding which vegetation would be better suited for maximizing the cooling effect during times with high energy demands.

METHODS

Study site

Berkeley and Oakland, California are situated in eastern side of the San Francisco Bay area. The two cities experience cool summers and mild winters with consistent fog inundation due to the upwelling in the ocean that occurs along the California coast. Berkeley and Oakland average roughly 27 inches of rain per year with July typically being the hottest month and January being the coldest. The two cities experience an average low temperature of 42 degrees Fahrenheit, and an average high temperature of 74 degrees Fahrenheit. There are over one hundred parks in the cities of Berkeley and Oakland, California ranging from baseball fields to lush green regional parks.

Figure 1. The black line shows the city borders of Oakland and Berkeley, California. The black polygons in the middle are the parks that were tested.

Data collection

This study examined 146 city and regional parks in Oakland and Berkeley (Figure 1) that are between 30 square meters and 82,000 square meters due to the 30 meter resolution constraint of the Landsat dataset. To find the park boundaries I extracted shapefiles from the city of Berkeley's website, Data.acgov.org, and Oakland's data catalogue. Within these shapefiles was information regarding the park name, area, and address.

For the imagery I used Landsat 8 OLI imagery which came from the United States Geologic Survey (USGS), specifically from the Level 1 (LT1) terrain-corrected Landsat product converted to top-of-atmosphere reflectance. The Landsat images of the East Bay fall in Path 44 and Row 34 and cover the whole study site of Oakland and Berkeley. I collected the Landsat images that are representative of Spring, Summer and Fall, from the following dates in 2014: March 18th, April 19th, May 21st, June 6th, June 22nd, July 8th, September 10th, October 12th, and October 28th. These dates were chosen due to the absence of cloud cover over the study site. In order to derive the Normalized Different Vegetation Index (NDVI) values, I performed a band math equation on the imagery using band 5 (Near-Infrared) and band 4 (red) to extract the proportional relationship between the two: ((Band 5-Band 4)/(Band 5+Band 4)). This provides a value between zero and one where higher NDVI values correspond to more photosynthetic activity. For the thermal intensity image, I used band 11 from the Landsat 8 OLI. Using these images and the aggregated park shape file, in ESRI's ArcGIS version 10.2 I used the zonal statistics tool to extract the mean, the minimum, the maximum, and the standard deviation NDVI and thermal intensity values for each park on each date.

Data analysis

I exported the zonal statistics table from ArcGIS into text files which were then exported into .csv files for further analysis. In order to understand the relationship between NDVI and thermal intensity within the parks, I performed two part analysis. I first performed a linear regression analysis on each dates' NDVI values versus their thermal intensity values as well as on the collective set of data points from all of the parks on all of the dates using the lines-plot function in the R statistical analysis software.

Secondly, to explore how the correlation between NDVI and thermal intensity varies over time I performed a Tukey's Range Test pair-wise comparison between the different seasonal slopes in the R software's R-commander package. For the Tukey's Range Test I split up the months into seasons: March, April and May were categorized as Spring. The two images in June and the image from July were categorized as Summer. Lastly, the September image and the two images from October were categorized as Fall.

RESULTS

Greenness-temperature correlation

I found a consistent, negative correlation between NDVI and surface temperature throughout all of the months. The linear regression using annual mean NDVI and thermal intensity values from each park indicated that NDVI levels explain 20% of the variance in thermal intensity based on the R^2 value of 0.2001 (**Figure 2**). As the sample year progressed from March 2014 to October 2014, NDVI values decreased while thermal intensity tended to increase (**Figure 3**). Single-variable linear regressions for each month demonstrated a significant (p-value < 0.001) and negative relationship between the two variables in each sampled month (**Table 1**). R^2 values ranged in size from 0.154 to 0.506, with the combined regression coefficient indicating that a 0.1 unit increase in NDVI would lead to a 1.18 degrees Kelvin decrease in surface temperature. (See **Appendix A** for a complete set of regression models for all months.)

Table 1. Monthly Results. This table displays the Equation of the regression line, the p-value, and R^2 value for each month.

Date	Equation of the Line	p-value	R^2 value
March 18th	$y = -8.48x + 295.45$	8.19e-12	0.280
April 19th	$y = -12.15x + 297.82$	2.2e-16	0.395
May 21st	$y = -14.13x + 301.30$	2.2e-16	0.506
June 6th	$y = -13.21x + 301.05$	2.2e-16	0.393
June 22nd	$y = -12.90x + 302.07$	2.2e-16	0.456
July 8th	$y = -8.37x + 297.48$	1.04e-6	0.154
September 10th	$y = -7.35x + 300.79$	2.21e-12	0.292
October 12th	$y = -6.60x + 300.03$	2.6e-11	0.268
October 28th	$y = -6.18x + 291.68$	9.33e-16	0.364
Combined Model	$y = -11.81x + 299.38$	**2.2e-16**	**0.200**

Using the park means from the different dates, I performed a linear regression where the p-value was 2.2e-16 and the R^2 value was 0.2001. **Figure 2** shows all of the relationship between NDVI and surface temperature for the parks in a hexagonal bin formation. The darker spots represent a higher density of parks that fall in that hexagonal value. Based on the graph and the significant p-value, I can reject the null hypothesis that there is no correlation. **Figure 3** demonstrates the change in NDVI and surface temperature with seasons based on the mean NDVI and surface temperature value for the whole dataset.

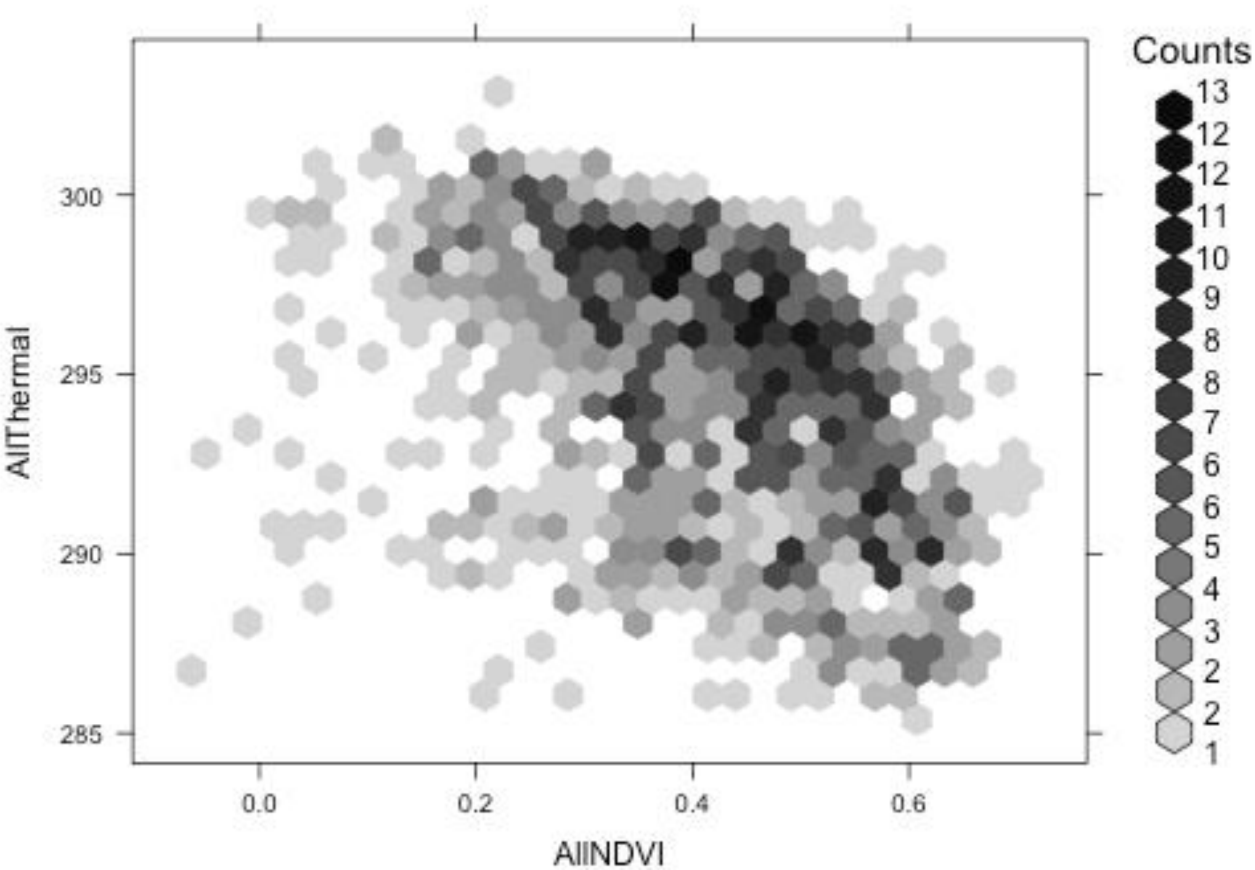

Figure 2. Overall Linear Regression: This graph is a hexagonal bin distribution graph where the darker the hexagon, the more parks there are the have the same NDVI and Thermal values.

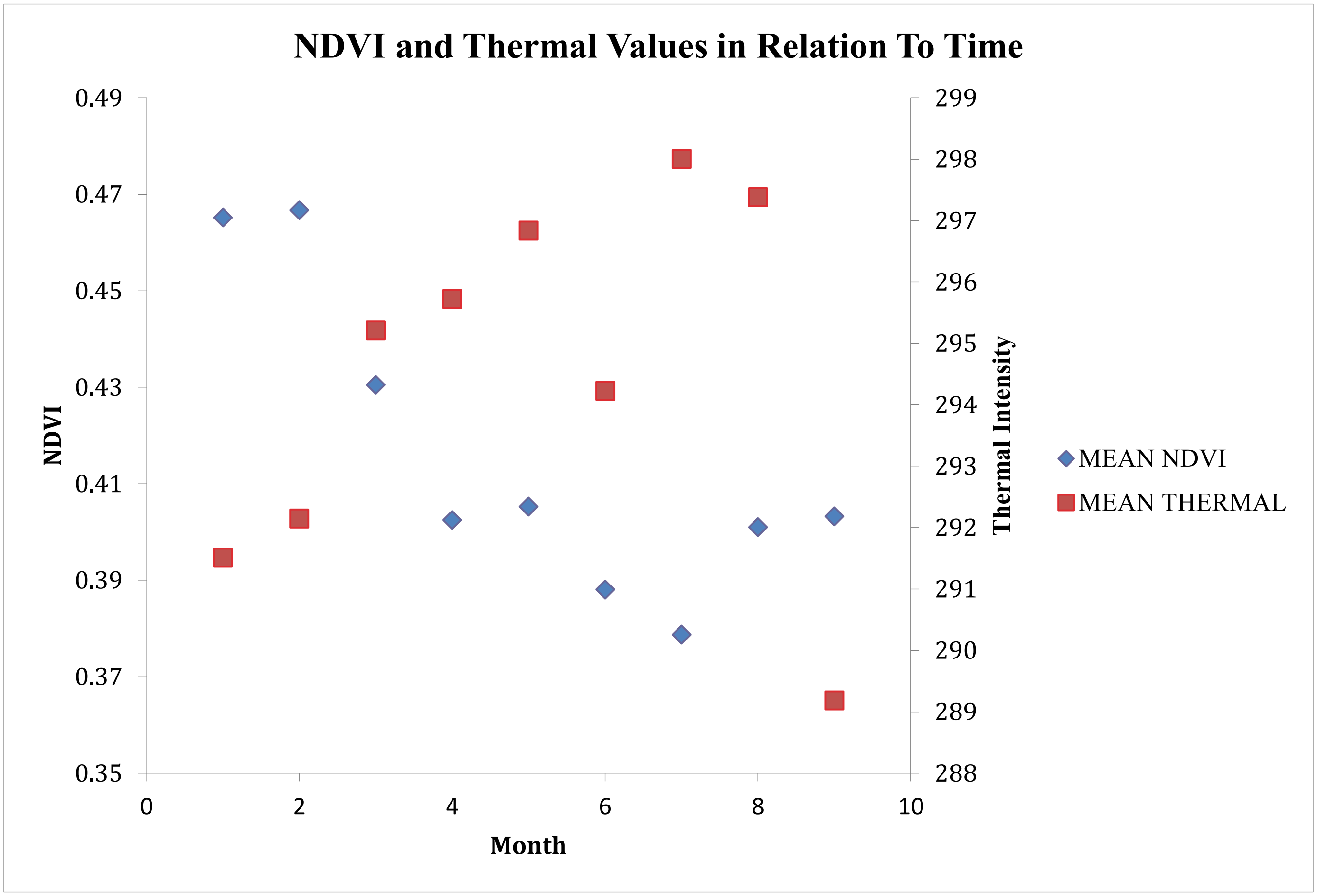

Figure 3. NDVI/Thermal Relationship Versus Time: This graph shows the changes in NDVI and surface temperature over time (the X-axis is month of the year).

Based on an initial visual assessment of **Figure 4**, I noticed a difference in the slope steepness primarily between the months. To statistically assess the variation, I used the Tukey's Range Test to perform a pair-wise comparison between the aggregated months into seasons and their collective slopes. Figure 4 shows the results of the pair-wise comparison with the p-value for the test being 0.0672. While this does not satisfy a p-value < 0.05, it does show that with a roughly 93% confidence level, there is some variation between seasons occurring. This indicates that there is variation amongst the seasons.

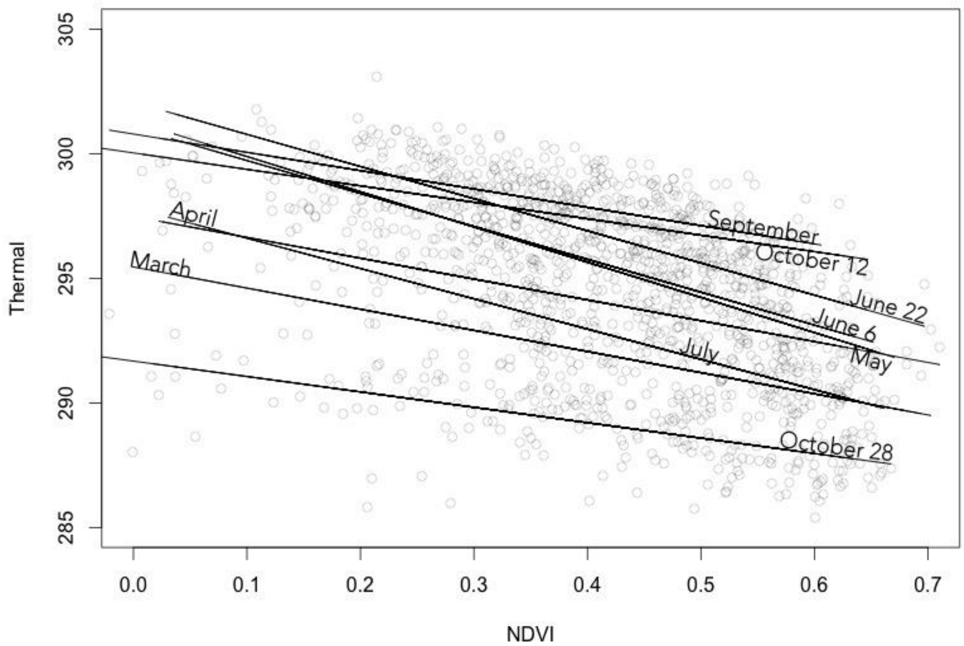

Figure 4. Seasonal NDVI/Thermal Intensity Relationship: This graph shows the individual months regression models plotted in a singular graph. The regression models were performed using the park values for NDVI and thermal intensity for each month individually.

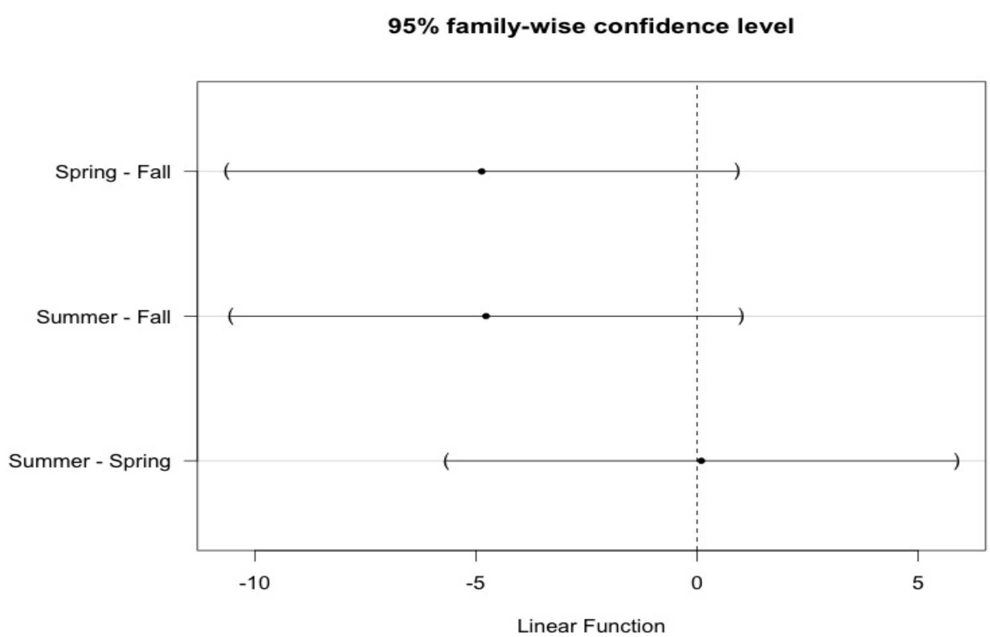

Figure 5. Tukey's Range Test Seasonal Comparison: This graph shows the results of the pair-wise comparison between the seasonal slopes. The p-value for this graph is 0.0672

DISCUSSION

With an expected global urban population growth of 2.5 billion people by 2050 (UN World Urbanization Prospects, 2014), the Urban Heat Island (UHI) effect is expected to increase as well due to increase in impervious surfaces and energy stresses from the built environment (Imhoff et al. 2010). Additionally, UHI mitigation strategies gain in importance as more awareness of the adverse human health implications of rising temperatures comes to light (McMichael et al. 2006). Increasing coverage of urban vegetation is one such potential mitigation strategy. By testing the Normalized Difference Vegetation Index (NDVI) against thermal intensity I was able to explore how differences in photosynthetic activity as represented by NDVI were correlated with a lower thermal intensity. The results of this study showed that thermal intensity is negatively correlated with NDVI and furthermore that this correlation varies between seasons. My findings suggest that it is valuable to utilize public green spaces as a tool for future urban planning due to the potential for thermal intensity reductions, as well as the indirect benefits for human health. This study, although limited in its spatial scope, serves to fortify previous understandings of the negative relationship between surface temperature and NDVI as well as to further understand how that relationship varies seasonally, specifically in Berkeley and Oakland, California.

Greenness-temperature correlation

The negative correlation between NDVI and thermal intensity implied that increasing the amount of vegetation will decrease thermal intensity within the parks. Since the mean NDVI and thermal intensity values were calculated for whole park polygons, it is likely that the monthly regression slopes were biased more positively in favor of parks with higher ratios of impervious surfaces to vegetated areas. By using parks that were previously delineated by the cities and the counties I was limited by the land cover types that already fell in those shapefiles. To improve the R^2 value, the vegetation and the impervious surfaces that are adjacent to one another, should be classified into separate categories and studied as separate entities. Imhoff et al. (2010) determined that with a further delineation of urban areas based on biome type, elevation and Impervious Surface Area, increasing the amount of impervious surfaces due to development primarily drives the increase in thermal intensity.

Other studies show the same trend between vegetated areas and surface temperature (Yu 2006; Weng 2004; Buyantuyev and Wu 2010; Chen et al. 2006), however they used metrics other than remote sensing such as localized ambient air instruments and Leaf Area Index to explore this relationship. While using metrics that require on the ground testing are accurate at the test location, they cannot account for large scale system-wide dynamics (Imhoff et. Al 2009). Using remote sensing allows for large scale studies of the relationship between thermal intensity and the desired vegetation metric can be derived from band compositions, which in this case was NDVI.

Seasonal variation

By visual and statistical comparison, the regression models for each month showed seasonal variation. Visually (Figure 4), it is apparent that the months of April, May and June showed steeper slopes when compared with the other months. Table 1 shows that April, May and June have the steepest slopes in addition to the highest R^2 values. With R^2 values for those months ranging from 0.393-0.506, roughly 40% to 50% of the thermal intensity value for those months can be explained by the values for NDVI. Additionally, Figure 5 shows the results for the Tukey's Range Test, which displays a nearly statistically significantly difference (p-value = 0.0672) in the slopes for the different seasons. This variation indicates that the correlation varies throughout the seasons. The lack of a statistically significant difference can be potentially attributed to the subjective nature of deciding which dates fall into which seasons in this case, such that there were an equal number of dates in each season. Additionally, if this analysis were to be performed over multiple years, the range test would have a larger sample size, and thus the p-value assigned would be more substantiated with evidence.

This seasonal variation has been shown in other studies (Lawrence & Slingo 2004) that explore the seasonal NDVI and thermal intensity relationship. With higher rates of evapotranspiration occurring during the summer months (Lawrence & Slingo 2004) helps to explain that increase in the R^2value, as with more evapotranspiration occurring more cooling occurs (Oliveira et al. 2011). The decrease in this cooling in the winter months has been previously attributed to both a lack of leaves for the evapotranspiration to occur through, in addition to the lack of leaves creating different shading effects as well as producing different sub-canopy soil reflectance patterns (Lawrence & Slingo 2004). While the vegetation has not been delineated in the study site parks as being evergreen and deciduous, it is safe to infer that based on the nature of parks as being recreationally based, evergreen trees do not dominate the landscape. Thus it is plausible that the shift in evapotranspirational processes due to variation in leaves is causing this less explanatory regression model for the winter months.

Limitations and future directions

The Urban Heat Island effect is a highly dynamic phenomena that varies from city to city and the intensity of the effect is impacted by a range of climatic properties that are native the site (Chen et al. 2006). Additionally, within a city, variation can occur based on the land types present in the city, even by a difference between a park and the sidewalk within the park (Oliveira et al. 2011). The large number of variables that contribute to the UHI effect reduce our ability to create a one-size-fits-all mitigation strategy primarily due to a current lack of a singular all encompassing understanding of the ways in which sites vary from one another. More specifically within this study, the physical scope of this study limits the implications to just the cities of Berkeley and Oakland as the physical characteristics such as being between a waterfront and a set of hills impacts the climate variables such as airflow, more than if the site were located on a flat plane. In the hopes of creating a better model to address the complex issues in urban remote sensing, it is important that the resolution of the imagery be high enough to help distinguish features at an object level, rather than multiple objects falling inside of one pixel. It has been suggested by another study (Weng et al. 2004), that spectral unmixing processes be utilized to help break down images into further components beyond the pixel size to account for more spatial variability within a single image.

Another limitation of this study is the use of NDVI as a metric for vegetation greenness. NDVI measures greenness topologically but provides no information on the density of the vegetation. Higher levels of vegetation biomass have been associated with lowering thermal intensity more, due the increased amount of evapotranspiration (Nichol & Lee 2005). Parks that are less for recreational use, such as tennis courts and soccer fields, are going to have higher levels of trees in comparison to grasses, which would mean that the NDVI values are most likely skewed for those parks. NDVI's underlying assumption that a consistent relationship holds between the amount of vegetation coverage and what is being represented by the outcome-pixel values, NDVI does not address vertical density heterogeneity. This inhibits creating a distinction between more dense urban forests impact on surface temperatures and thinner urban forests. Future studies might consider using newer high resolution three-dimensional mapping tools, which capture both the physical properties of the land cover, as well as the Red, Green and Blue wavelengths (Dandois & Ellis 2013). This could be useful for looking at parks in the future, as with more dense vegetation, the surface level imagery cannot fully capture what kind of impact that vegetation could potentially have.

Examining the relationship between NDVI and thermal intensity provided a good understanding of one potential UHI mitigation strategy. However, there are other questions that should be explored in order to further our understand of UHIs. Some questions, for example, are: How does airflow impact the travel of lower surface temperatures from highly vegetated areas to more built areas; Is there a buffer at which the impacts of cooler surface temperatures do not continue; What is that buffer; Does the size of the cluster of vegetation as well as the distance between vegetation clusters impact the effectiveness of the cooler surface temperatures; How do these relationships vary during years of drought? Using these research questions, a more holistic understanding of UHI mitigation strategies can be created and more informed urban planning design can come into fruition.

Broader implications

As urban densification continues to increase, the need to preemptively address Urban Heat Island Effect via mitigation strategies grows increasingly important. With regional implications regarding energy demand, air quality, and public health (Rosenzweig 2006), the data showed that during the times of peak energy demand in summer (Newsham & Bowker 2010), the correlation between NDVI and thermal intensity was the strongest. This means that vegetation can help mitigate the Urban Heat Island effect in Berkeley and Oakland during the most critical months. Additionally, vegetation has been shown to, through its evapotranspiritive processes, to cool the air and slow down photochemical reactions, in addition to reduce pollutants in the air (Taha 1996).

Specific recommendations can be made in the cities of Berkeley and Oakland, to increase the amount of green spaces, favoring woody vegetation, in the cities to reduce the surface temperature by, on average, another 1.18 degrees for every 0.1 increase in NDVI. Management strategies need to be further explored, as the types of vegetation have shown to have an impact on the pollution aspect of the urban ecosystem. With some types of vegetation increasing the amount of hydrocarbons in the air which create ozone (Taha 1995), the types of vegetation that are put in have an effect on overall health of the urban atmosphere.

In addition to the UHI mitigation effects, there are socio-economic benefits to increasing the amount of trees in urban areas such as increased economic investment in lower income neighborhoods (Iverson & Cook 2000). Lastly, the notion of biophilia, that humans have a high affinity for green areas, such that it increases happiness (Kellert & Wilson, 1995), is another positive implication of increasing green spaces.

This study has shown that based on the negative correlation between NDVI and thermal intensity, management strategies should be developed to mitigate the Urban Heat Island in Berkeley and Oakland that incorporate more vegetation into currently existing parks, as well as that create more parks to aid in this overall cooling process. Additionally, the seasonal shifts in the relationship NDVI and thermal intensity can be further exploited to help mitigate the UHI effects during the summer when we see the high energy demands that perpetuate the UHI effects. Furthermore, there are more nuances associated with this study that need to be explored in order to maximize the benefits of the vegetation both environmentally and economically. This study aimed to fortify the previous research on vegetation as an Urban Heat Island effect mitigation strategy, and to hopefully add to our understanding surrounding the benefits of our city parks to go beyond just recreational value, and to recognize that the park system could have a net positive effect on UHI mitigation.

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APPENDIX A: Regression Models

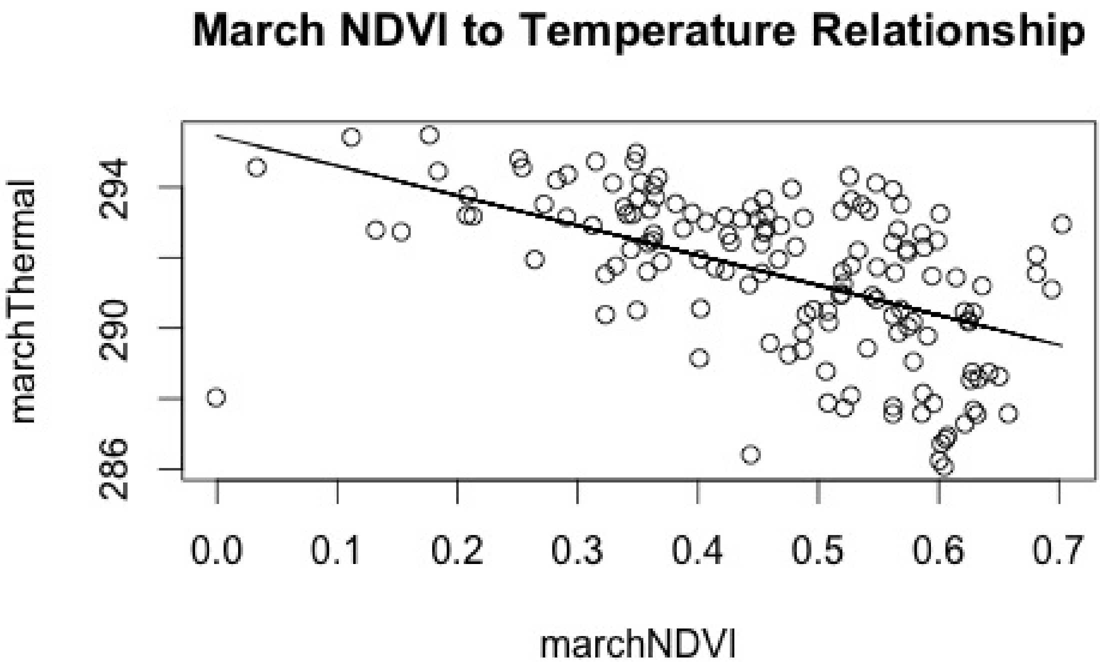

Figure A1. March NDVI/Temperature Correlation: This graph shows the linear regression for the image from March 18th. The equation of the line is $y = -8.48x + 295.45$

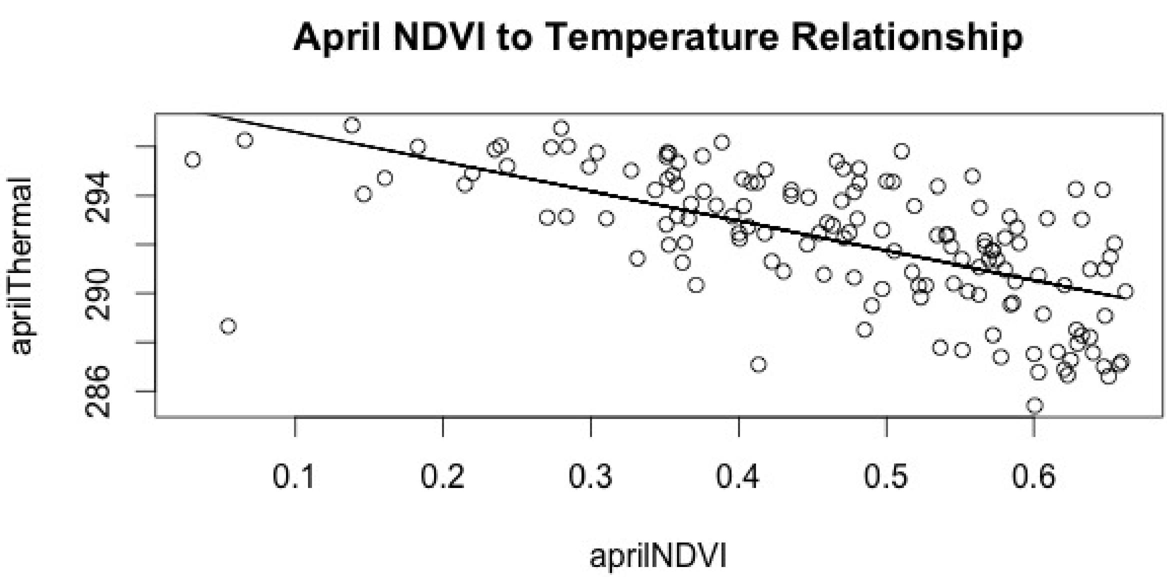

Figure A2. April NDVI/Temperature Correlation: This graph shows the linear regression for the image from April 19th. The equation of the line is $y = -12.15x + 297.82$

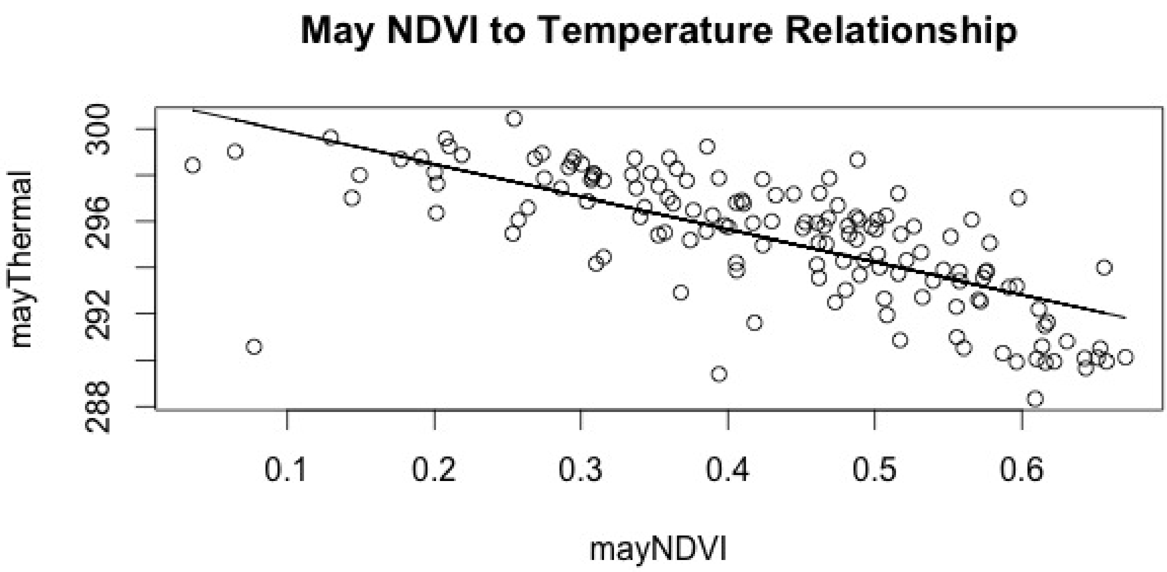

Figure A3. May NDVI/Temperature Correlation: This graph shows the linear regression for the image from May 21st. The equation of the line is $y = -14.13x + 301.30$

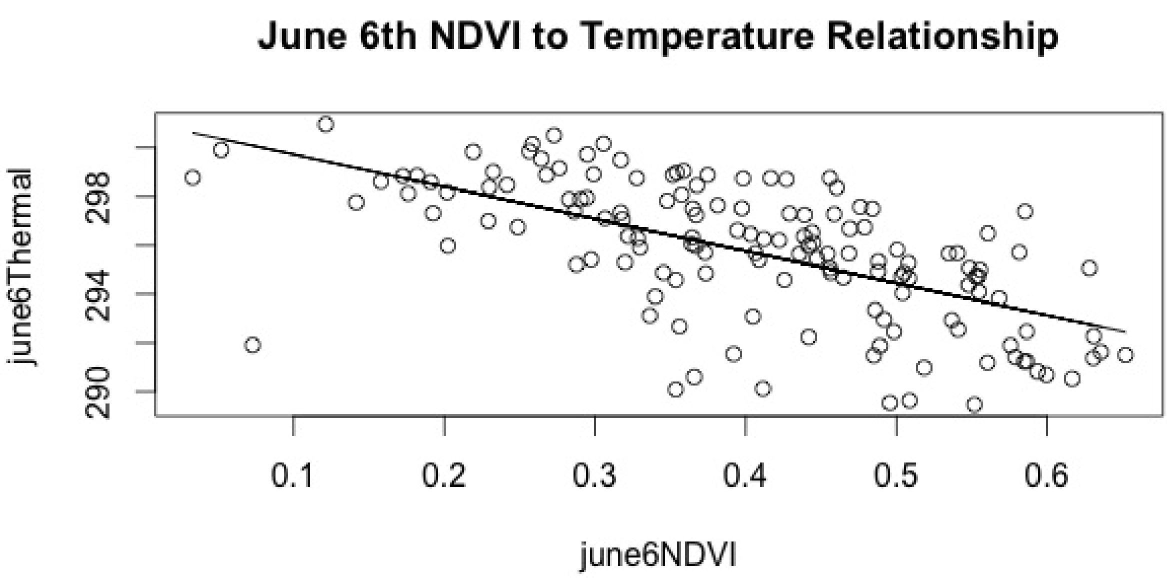

Figure A4. June 6th NDVI/Temperature Correlation: This graph shows the linear regression for the image from June 6th. The equation of the line is $y = -13.21x + 301.05$

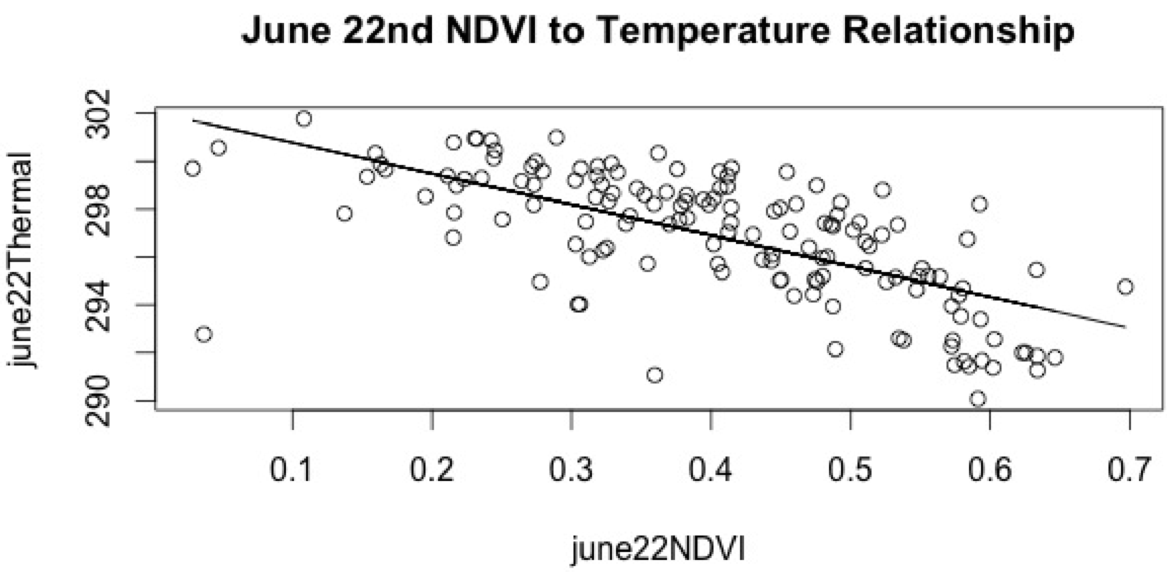

Figure A5. June 22nd NDVI/Temperature Correlation: This graph shows the linear regression for the image from June 22nd. The equation of the line is $y = -12.90x + 302.07$

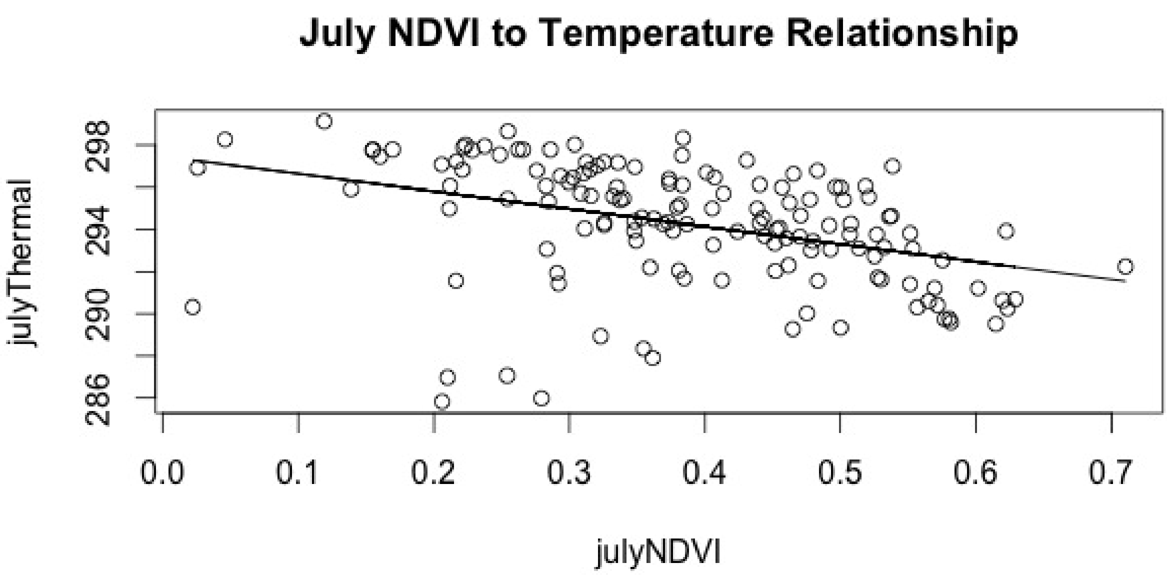

Figure A6. July 8th NDVI/Temperature Correlation: This graph shows the linear regression for the image from July 8th. The equation of the line is $y = -8.37x + 297.48$

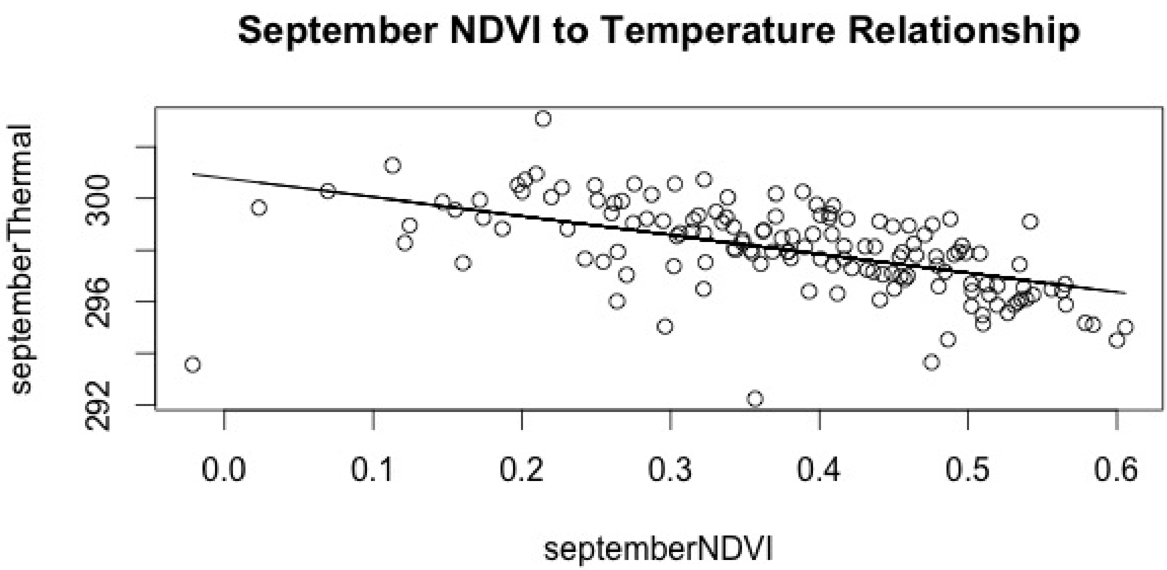

Figure A7. September 10th NDVI/Temperature Correlation: This graph shows the linear regression for the image from September 10th. The equation of the line is $y = -7.35x + 300.79$

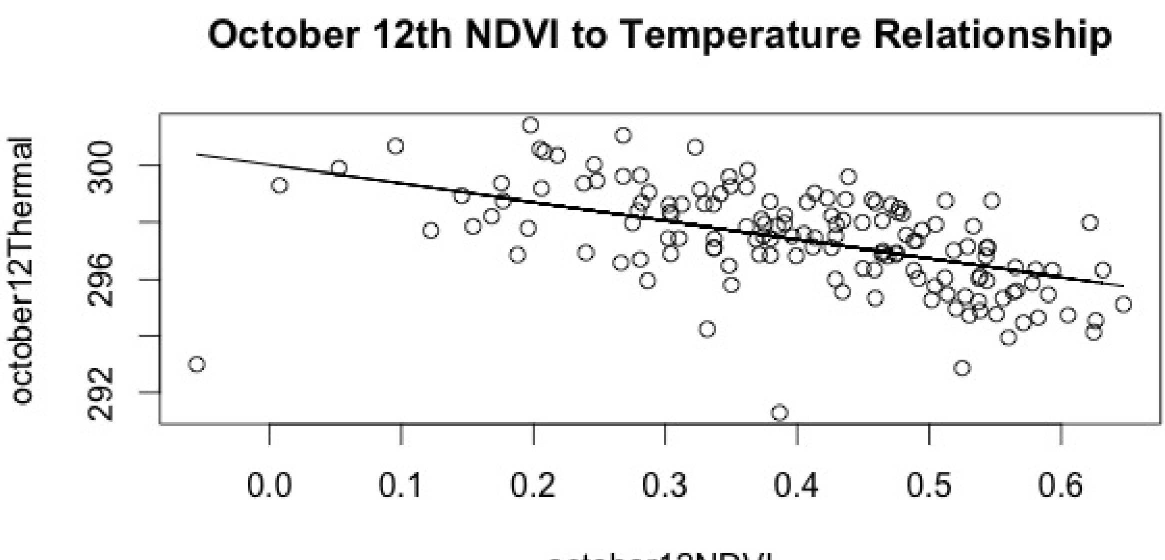

Figure A8. October 12th NDVI/Temperature Correlation: This graph shows the linear regression for the image from October 12th. The equation of the line is $y = -6.60x + 300.03$

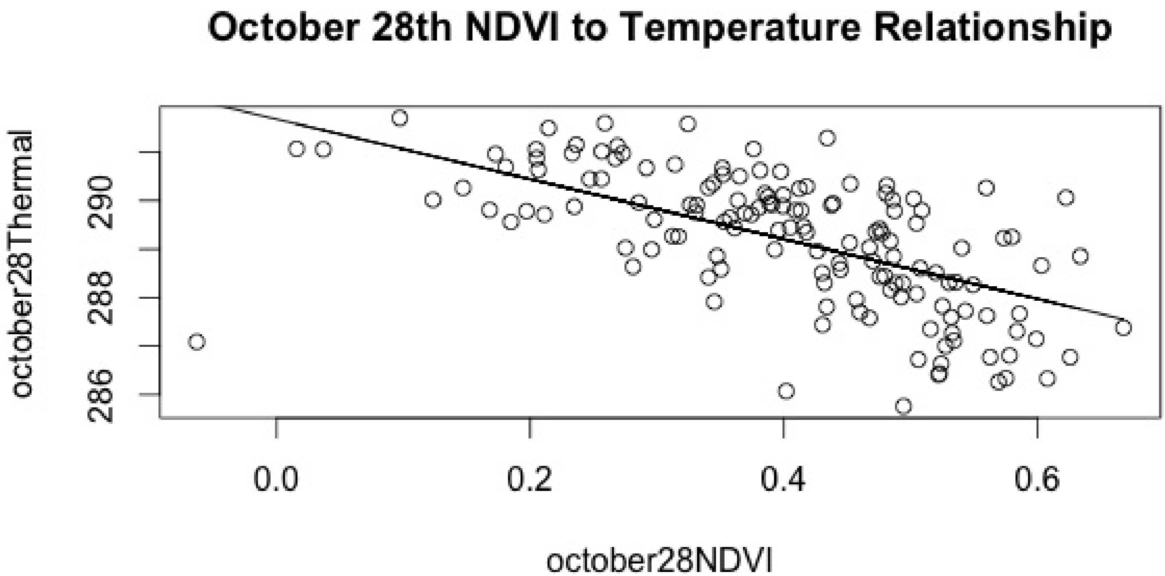

Figure A9. October 28th NDVI/Temperature Correlation: This graph shows the linear regression for the image from October 28th. The equation of the line is $y = -6.18x + 291.68$